FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

Functional Gait Assessment in Fall Prevention Exercises

Teresa Isabel Faria Moleiro

MESTRADO INTEGRADO EM BIOENGENHARIA

Supervisor at FEUP: Diamantino Freitas, PhD

Supervisor at Fraunhofer AICOS: Dinis Moreira, MSc

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Resumo

A população mundial está a envelhecer pelo que o desenvolvimento de soluções que ajudem as populações a manter a sua qualidade de vida e saúde é essencial para as sociedades atuais. As quedas na população idosa são um problema de saúde pública em crescimento. Cerca de um terço da população sénior cai por ano, e as quedas nessa população são uma fonte significativa de morbilidade e mortalidade. Vários factores de risco de queda já foram identificados e enquanto alguns, como a idade, não podem ser evitados, outros, como a falta de exercício, podem ser modificados de forma a diminuir o risco de queda. De entre as estratégias de prevenção de quedas propostas nas últimas décadas, os programas de exercício físico têm mostrado bons resultados na diminuição do risco e da taxa de quedas.

A análise de marcha pode ser usada para avaliar problemas na marcha e o risco de queda. Normalmente, os métodos de análise de marcha são baseados em observações feitas por um especialista ao ver o seu paciente a andar, mas estes métodos são pouco precisos e objectivos. Em relação a métodos objectivos, sistemas de captura de imagem são o *gold standard*. Contudo, este método necessita de equipamento caro, pessoal treinado, laboratórios especializados e é um processo lento. Outros sensores, como sensores de força e pressão, acelerómetros, giroscópios e combinações destes, também já foram propostos como alternativas para analisar a marcha. A maioria dos métodos de análise de marcha propostos anteriormente só avaliam exercícios de marcha livre e não são capazes de analisar outros exercícios mais complexos e desafiantes. Estes poderiam fornecer mais informação útil aos profissionais de saúde.

Nesta dissertação, a análise de marcha foi realizada usando sistemas inerciais em cinco exercícios do *Otago Exercise Programme*: andar para trás, andar pé-ante-pé, andar pé-ante-pé para trás, andar apoiado nos calcanhares e andar apoiado nas pontas dos pés. Foram recolhidos dados de um grupo de 14 idosos e de um grupo de 14 jovens adultos. Parâmetros da marcha como o número de passos, a sua duração e o tamanho de cada um foram determinados e comparados com as gravações dos participantes a realizarem os exercícios. Em geral, a deteção de passos teve sucesso com um erro relativo que variou entre 4 e 8% em relação a passos não detectados e 1 a 2% de passos detectados erradamente. A determinação dos limites das fases de marcha teve um erro relativo de 1% e a duração do passo teve um erro relativo de 6%. A deteção da viragem poderia ser melhorada uma vez que a sua duração teve um erro relativo que variou entre 32 e 44%. O cálculo do tamanho do passo não foi bem sucedido e teve um erro relativo máximo de 83%.

Pârametros de marcha relacionados com a aceleração, velocidade angular e ângulo entre a porção inferior da perna e a vertical também foram calculados e comparados entre grupos. Estas comparações sugerem que esses parâmetros poderiam ser usados para distinguir entre grupos. Para além disso, os resultados das comparações também sugerem que diferentes exercícios podem expor diferentes dificuldades de marcha e poderiam fornecer mais informação aos profissionais de saúde que os exercícios de marcha livre. Comparações entre os dois membros inferiores do mesmo participante também foram feitas e também sugerem que a avaliação de diferentes exercícios poderia fornecer mais informação. Para além disso, também sugerem que poderiam ser úteis

para identificar problemas nos membros inferiores e avaliar o sucesso do programa de exercício.

Abstract

The world population is ageing. Therefore, the development of solutions to help people maintain their quality of life and health is essential for contemporary societies. Older adult falls is a growing public health problem. About one-third of the older adults fall each year, and falls in the elderly population are a significant source of morbidity and mortality. Several risk factors have already been identified, and while some of them, such as age, cannot be prevented, others, such as lack of exercise, can be modified to reduce fall risk. Between the fall prevention strategies proposed in the last decades, exercise programmes showed good results in diminishing fall rates and fall risk.

Gait analysis can be used to assess walking disabilities and fall risk. Gait analysis methods are usually based on observations made by specialists during walking exercises performed by the patient, but these methods lack accuracy and objectivity. Regarding objective methods, the gold standard is video-based motion capture; however it requires expensive equipment, trained personnel, specialised laboratories, and it is time-consuming. Other sensors, such as force and pressure sensors, accelerometers, gyroscopes and combinations of these, were also presented as alternatives to perform gait analysis. Most of the previously proposed gait analysis methods only evaluate free walking exercise and are not able to analyse more complex and challenging exercises that may provide more useful information to the healthcare professionals.

In this dissertation, gait analysis was performed using inertial measurement units on five exercises from the Otago Exercise Programme: backwards walking, tandem walking, tandem walking backwards, heel walking and toe walking. Data were collected from a group of 14 older adults and a group of 14 younger adults. Gait parameters such as the number of strides, stride time and stride length were determined and compared to the video-recordings of the participants performing the exercise. In general, detection of strides was successful with a 4-8% relative error of non-detected strides and 1-2% of over-detected strides. Determination of the gait phase limits was achieved with a 1% relative error and the stride time had a relative error of 6%. Turn detection could be improved as the turn duration had a relative error varying between 32 and 44%. The stride length estimation was not successful with a maximum relative error of 83%.

Gait parameters related to the acceleration, the angular velocity and the shank-to-vertical angle were also computed and compared between groups. Inter-group comparisons suggest that these parameters could be used to distinguish between groups. Moreover, those comparisons results also suggest that different exercises could expose different walking difficulties and, therefore, could provide more information to healthcare professionals than free walking exercises. Intra-individual comparisons of the computed gait parameters were also performed. These comparisons results also suggest that the use of different walking exercises in gait assessment could provide more information. Furthermore, intra-individual comparisons suggest that they could be used to identify impaired limbs and evaluate the success of the exercise programme.

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Não poderia terminar esta etapa tão importante sem agradecer a quem me ajudou a chegar aqui. Em primeiro lugar, gostaria de agradecer à Faculdade da Engenharia da Universidade do Porto por toda a formação e educação que me proporcionou ao longo dos últimos 5 anos. Aos meus orientadores, o professor Diamantino Freitas, da FEUP, e o Dinis Moreira, da Fraunhofer AICOS, por todo o apoio dado ao longo deste projecto. À Fraunhofer AICOS pelas instalações e material disponibilizado, sem os quais não teria sido possível o desenvolvimento deste projecto. A todos os voluntários que me ajudaram dando um bocadinho do seu tempo para participar nas recolhas de dados.

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Teresa Moleiro

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Abbreviations and Symbols

3D	three-dimensional
AFO	Ankle-foot orthosis
ANCOVA	Analysis of covariance
ANOVA	Analysis of variance
CDC	Centers for Diseases Control and Prevention
CoP	Center of pressure
CoV	Coefficient of variation
DTW	Dynamic time warping
ELGAM	Extra-Laboratory Gait Assessment Method
EMG	Electromyography
EN	End of non-stationary phase
FaME	Falls Management Exercise
GARS	Gait Abnormality Rating Scale
GC	Gait cycle
GNSS	Global navigation satellite systems
GRF	Ground reaction force
HMM	Hidden Markov Models
IMU	Inertial Measurement Unit
LiFE	Lifestyle Approach to Reducing Falls Trough Exercise
MSWS-12	Multiple Sclerosis Walking Scale
POMA	Tinetti Performance-Oriented Mobility Assessment
PSD	Power spectral density
RI	Ratio index
SA	Symmetry angle
SEFIP	Senior Fitness and Prevention
SI	Symmetry index
SN	Start of non-stationary phase
SVA	Shank-to-vertical angle
T25-FW	Timed 25-Foot Walk
TUG	Timed Get up and Go
WHO	World Health Organization
ZUPT	Zero veocity updates

Chapter 1

Introduction

The world population is ageing. Technological advancements in healthcare over the last decades contributed to the increase of life expectancy by improving medical treatments and lowering treatment costs. Nevertheless, a higher percentage of older adults creates some challenges for societies. The elderly population is frailer and is more affected by health issues. Therefore, this population requires more support from families, communities and healthcare systems (He et al., 2016). Ultimately, societies may need to adjust healthcare systems and retirement policies to maintain their sustainability. Technology advancements in the field of medicine and others can also help people maintain health and quality of life and preventing negative consequences of ageing. Despite all the achievements already accomplished, more efforts should be made to help older populations live a longer and healthier life.

1.1 Problem Description and Motivation

Older adult falls are a growing problem in contemporary societies. The frequency of fall events increases with risk factors such as age and mobility impairments. These events are a significant source of morbidity and mortality as their consequences generally include functional disabilities, increased fear of falling, reduction of self-confidence, social isolation and, in extreme situations, death. Fall risk factors were already identified which lead to the creation of a series of fall prevention interventions. Most of the successful ones include exercise programmes to improve balance and strength (World Health Organization, 2008).

Gait analysis can provide useful indicators of mobility disorders, help diagnose some pathologies and assess each person's fall risk. In the rehabilitation field, gait analysis can give informations to healthcare professionals to evaluate the patient's difficulties and improvements over time. In current practice, observation-based methods are normally used to assess patients gait and consist in analyses carried out by a specialist that evaluate gait parameters by observing the patient walking in clinical conditions. These methods are easy-to-use and low-priced, however, they lack accuracy and objectivity (Muro-de-la Herran et al., 2014).

There are already several techniques that can be used to perform objective gait analysis. The gold standard is video-based motion capture. Nonetheless, this system needs specialised laboratories, trained personnel and expensive equipment which may restrict the population's access to this technique. Other objective methods based on electromyography signals and force sensors were proposed as an alternative to perform gait analysis, but the most promising methods use inertial sensors such as accelerometers and gyroscopes. Inertial sensors can be used alone or integrated in inertial measurement units (IMUs). IMUs are generally considered to be easy-to-use, low-cost, non-invasive, wearable, and allow the measurement of relevant gait parameters under real-life conditions without most of the usual laboratory restrictions (Muro-de-la Herran et al., 2014).

Independently of the used method, most gait analysis systems are only used with free walking exercises and are not able to analyse more complex and challenging exercises. Evaluation of such exercises could provide more useful information for healthcare professionals than regular ones contributing to a better assessment of the patient.

1.2 Dissertation Goal

The goal of this dissertation is to analyse functional gait exercises selected from the Otago Exercise Programme using IMUs. From the analysis of those exercises, it is expected to obtain meaningful measures that could provide useful information for healthcare professionals.

1.3 Document Structure

This document presents the work performed in this dissertation, and it is organised in six chapters.

The present chapter, Chapter 1, introduces the motivation and goal of the dissertation.

In Chapter 2, older adults falls are discussed. Fall risk factors, socio-economic impact and fall risk assessment are introduced. Moreover, some strategies to prevent falls including several prescribed fall-related exercise programmes are presented.

In Chapter 3, gait analysis is introduced. A normal cycle of gait is described along with some objective and subjective gait analysis methodologies. State-of-the-art gait analysis methodologies using IMUs and in functional walking exercises are also analysed and discussed.

Chapter 4 presents the methodology followed for the analysis of the selected functional gait exercises.

In Chapter 5, the results obtained are presented and discussed.

Chapter 6 presents the conclusions and the future work that could be done to improve the work performed in this dissertation.

Chapter 2

Falls and Their Prevention

World population is ageing as a result of an increase in people's longevity. In 2015, among the 7.3 billion worldwide population, 8.5% were aged 65 and over. It is expected that, by 2050, the elderly population will represent 16.7% of the global population (He et al., 2016). The older population has more health issues, such as dementia, stroke consequences, cancer and fractured hips, which are associated with an increase in costs for healthcare systems (He et al., 2016). This trend is also present in the Portuguese population. Between 2001 and 2011, the population's average age increased 2.82 years and the percentage of the elderly population changed from 16.30% to 19.03% (Instituto Nacional de Estatística, 2011).

Therefore, maintaining the quality of life associated with a healthy life at advanced ages is of growing importance. If adults reach older age in a healthier condition and with a better life quality, the probable adverse effects of the population ageing, could be attenuated. These effects are related to the need for adjustments in healthcare systems and retirement policies to maintain their sustainability.

2.1 Definition of Fall

Different definitions of falls are used in different studies, but they can be commonly defined as "inadvertently coming to rest on the ground, floor or other lower level, excluding intentional change in position to rest in furniture, wall or other objects" (World Health Organization, 2008). The use of different definitions of falls complicates the comparison between studies and reporting of those events. Older people may have a different concept of fall when compared with researchers or healthcare professionals. For example, older people may count a loss of balance as one fall and healthcare professionals may only be interested in events that caused injuries (World Health Organization, 2008).

People can be classified according to the number of falls in a defined amount of time or in terms of fall frequency. Usually, a faller is someone who has fallen at least one time in the defined time period. A recurrent faller is someone who has fallen two or more times in the same period. These definitions may also vary between studies (Masud and Morris, 2001).

2.2 Fall Risk Factors

Falls can be appreciated as a result from the interaction of several causes and risk factors. These can be divided into several categories such as intrinsic or extrinsic and can also be grouped into four dimensions: biological, behavioural, environmental and socio-economic factors. Table 2.1 shows a list of fall risk factors.

Biological factors include characteristics such as age and gender. Ageing is associated with changes in gait and balance, more severe chronic conditions and increased prescription of medication (Bergen et al., 2016; Stevens et al., 2012). Even though not all medications increase fall risk, the use of four or more drugs or the use of psychotropic drugs may make older adults more prone to falls (Tromp et al., 2001).

Behavioural risk factors include those concerning human actions or emotions and are potentially modifiable. For example, in some cases, the intake of multiple medications can be modified by adjusting the prescription according to medical advice (World Health Organization, 2008).

Environmental risk factors are related to hazards that surround older people. These include home hazards such as those caused by narrow steps or looser rugs and public spaces dangers such as uneven sidewalks or poor lightning (World Health Organization, 2008).

Finally, socio-economic risk factors are those related to the influence of social and economic status. For example, a low income can limit a patient's access to healthcare preventing the treatment of health problems associated with a higher risk of falling. Therefore, low incoming patients may have a higher risk of falling injuries (World Health Organization, 2008).

Table 2.1: Fall risk factors (World Health Organization, 2008)

Biological	• Age and gender • Multiple medication use • Chronic illnesses • Physical, cognitive and affective capacities decline • Muscle weakness • Postural hypotension
Behavioural	• Multiple medication use • Excess alcohol intake • Lack of exercise • Inappropriate footwear
Environmental	• Poor building design • Home hazards such as slippery floors, stairs and looser rugs • Public space hazards such as insufficient lightning and cracked or uneven side walks
Socio-economic	• Low income and education levels • Inadequate housing • Lack of social interactions • Limited access to health and social services • Lack of community resources

2.3 Socio-economic Impact

Older adult falls are a growing public health problem. Approximately one-third of community-dwelling people over 65 years of age fall each year (Howcroft et al., 2013; Tromp et al., 2001). The frequency of falls is even higher in older people who live in nursing homes (World Health Organization, 2008). Older adult falls are a significant source of morbidity and mortality. In the United States, falls are the leading cause of fatal and non-fatal injury among people aged 65 years and over. In the 2014 Behavioural Risk Factor Surveillance System survey, 28,7% of older adults (aged 65 years and over) reported falling, at least one time, in the previous year. An estimate of 29.0 million falls occurred resulting in a fraction of 7.0 million requiring medical treatment or restricting activity at least for one day. Also in 2014, 2.8 million patients were treated in emergency departments due to fall-related injuries, and 800 thousand of those patients were hospitalised. In the same year, approximately 27 thousand older adults died due to falls (Bergen et al., 2016). The incidence of falls increases with age and is higher in women. However, rates of fatal falls among men are higher than for women. (World Health Organization, 2008)

The consequences of falls in older adults are more severe than in younger patients (Sterling et al., 2001). More than half of injuries sustained by 70 years or older patients are the result of falls and approximately 40% of admissions in nursing homes are related to falls (Sterling et al., 2001). Other consequences of falls include an increase of fear of falling, long-term disability, and a reduction of activity, mobility levels and self-confidence. Older people commonly report fear of falling. This fear can motivate some people to take precautions and adopt strategies to avoid falling. For others, fear can lead to a cyclical pattern of mobility deterioration, social isolation and declining quality of life even if the person has not suffered a fall (Howcroft et al., 2013; World Health Organization, 2008).

Healthcare impacts and costs of falls in older adults are increasing. Those costs can be divided into two categories: direct and indirect costs. Direct costs include the costs associated with medical resources utilisation such as medication and hospitalisation. The average cost of hospitalisation due to a fall-related injury ranges from US$ 6 600 in Ireland to US$ 17 000 in the US. Indirect costs result from the loss of work productivity of the patient and caregivers. In the United Kingdom, the average lost earnings are approximately US$ 40 000 per year per household (World Health Organization, 2008).

2.4 Fall Risk Assessment

Although falls are a common problem, less than half of the older adults who fall discuss those situations with their healthcare provider. The appointed reasons include fear of losing independence and recall bias because they may forget or not report falls that did not cause injuries. Women were found to be more prone to report falls to their doctors and discuss fall prevention than men. Taking this into consideration, doctors or other healthcare providers should ask older patients about previous falls and discuss fall prevention with them (Stevens et al., 2012).

Given the multiple risk factors, fall risk assessment should include factors such as medical history, recent falls, gait and balance evaluation and assessment of other pathologies (Axer et al., 2010). The 2010 American Geriatrics Society/British Geriatrics Society Clinical Practice Guideline for Prevention of Falls in Older Persons (Drootin, 2011) recommends a multi-factorial risk assessment for older adults who present a fall or have gait and balance problems. According to those guidelines, fall risk assessment should start by asking the person about recent falls and their frequency and discussing difficulties in gait and balance. If the patient answers positively, that person is included in a high-risk group, and more factors should be assessed. If the person has fallen only one time (in the last year) but shows no abnormalities in gait and balance, only periodic reassessment is needed. Otherwise, the healthcare professional should evaluate the patient's medical history and perform some physical, cognitive and functional assessments. According to the obtained results, different interventions may be prescribed (Drootin, 2011).

2.5 Falls Prevention Interventions

Most falls in the elderly population could be avoided. Health care professionals are a crucial element in this process by discussing the problem with their patients and suggesting appropriate interventions (Bergen et al., 2016). Fall prevention can work by minimising some risk factors. Not all risk factors are modifiable, but some behavioural and environmental risk factors can be improved. For example, in a study of McKiernan (2005), the use of non-slip footwear in hazardous winter conditions reduced the rate of outdoor falls. The success of any interventions to minimise the risk of falling is dependent on the beliefs, attitudes, and behaviour of older people, health care professionals and the community where the person lives. Older people need to have the ability and willingness to change their habits and perceive that those changes are beneficial to them. Those changes can be encouraged by family members and healthcare professionals. Common beliefs such as the perception that falls prevention is only for very old or disabled people and that it consists of activity restriction and loss of independence should be changed. According to the World Health Organization (WHO)'s Global Report on Falls Prevention in Older Age (World Health Organization, 2008), the awareness of interventions that can improve balance and prevent falls should increase. Those interventions should be publicised by promoting benefits fitting a positive self-identity and be designed to meet the needs, preferences and capabilities of each person.

Many prevention programmes have been established and evaluated. The proposed interventions include exercise and education programmes, medication optimisation and environmental modifications. A review by Gillespie et al. (2012) compared the results of several published fall prevention interventions and concluded that exercise programmes were effective in reducing the rate of falls and the risk of falling whether they were delivered in group classes or individually prescribed at home. Successful exercise programmes commonly include multiple exercise categories such as balance retraining and muscle strengthening. Concerning medication-related interventions, vitamin D supplementation only appeared to be effective in people who had a vitamin D deficiency. Medication review and gradual withdrawal showed results if the medication was psychotropic. Surgical treatment of pathologies such as carotid sinus hypersensitivity with pacemakers and removal of eye cataracts also reduced the rate of falls. Home safety interventions were effective in reducing the rate of falls and risk of falling, specially if occupational therapists delivered them. Interventions consisting of nutritional supplementation, psychological or educational interventions did not show effects in reducing the rate of falls. Fall prevention programmes can also consist of multiple interventions in several categories. Most of the effective multiple interventions included exercise programmes (Gillespie et al., 2012).

These conclusions are concordant with the 2010 American Geriatrics Society/British Geriatrics Society Clinical Practice Guideline for Prevention of Falls in Older Persons (Drootin, 2011). The guidelines recommend medication minimisation, initiation of customised exercise programmes, treatment of vision impairments and cardiovascular disorders, management of foot and footwear problems, modifications in the home environment and patient education and information (Drootin, 2011).

2.5.1 Fall Prevention Exercise Programmes

Several exercise programmes have been proposed to prevent falls. Between those that have published evidence of their effect in reducing falls, the Centers for Disease Control and Prevention (CDC) recommends 14 (Stevens, 2010). A comparison between them is presented in Table 2.2. The Otago Exercise Programme is described in more detail in the following section.

Table 2.2: Comparison between Fall Prevention Exercise Programmes (Stevens, 2010)

Programme	**Reduction in Fall Rates or Fall Risk**	**Description**
Simplified Tai Chi (Wolf et al., 1996)	47% reduction in the fall risk	• Improvement of strength, balance and walking speed • Group classes and individual sessions with a Tai Chi instructor and individual practice sessions • 25-minutes group sessions twice a week, 45-minutes individual practice with an instructor once a week and 15-minute individual practice sessions twice a day during 15 weeks
Veterans Affairs Group Exercise Program (Rubenstein et al., 2000)	66% less likely to fall	• Improvement of strength, endurance, mobility and balance • Group classes delivered by exercise physiology graduate students with training or physical therapists • One hour and half sessions three times a week for 12 weeks
Australian Group Exercise Program (Lord et al., 2003)	Fall rate was 22% lower in all participants and 31% lower in participants who had fallen in the previous year	• Improvement of strength, coordination, gait, balance and ability to carry out daily activities • Group classes delivered by trained instructors • One-hour classes twice a week for 12 months
Stay Safe, Stay Active (Barnett et al., 2003)	40% less likely to fall	• Improvement of balance, coordination, strength, reaction time, and aerobic capacity

Table 2.2: Comparison between Fall Prevention Exercise Programmes (Stevens, 2010)

Programme	**Reduction in Fall Rates or Risk**	**Description**
		• Group sessions with additional exercises performed at home delivered by accredited exercise instructors • Total of 37 one-hour classes once a week
The Otago Exercise Programme (Campbell and Robertson, 2003)	35% reduction in fall rate	• Improvement of balance and strength • Individual sessions at home with exercises prescribed by an instructor • 30 minutes exercise sessions three-times a week and 30 minutes walking sessions twice a week during one year
Falls Management Exercise (FaME) Intervention (Skelton et al., 2005)	31% reduction in fall rate	• Improvement of balance and strength • Group classes and individually prescribed home exercises • Weekly one-hour group classes and 30 minutes of home exercises twice a week for 36 weeks
Tai Chi: Moving for Better Balance (Li et al., 2005)	Risk of multiple falls decreased 55%	• Improvement of balance and physical performance • Group classes delivered by Tai Chi instructors. Practice at home was encouraged • One-hour classes three-times a week for 26 weeks
Erlangen Fitness Intervention (Freiberger et al., 2007)	23% fewer falls	• Improvement of functional skills, strength, endurance, and flexibility • Group sessions delivered by two trainers and exercises at home • One-hour group classes twice a week during 16 weeks and daily home exercises
Central Sydney Tai Chi Trial (Voukelatos et al., 2007)	33% reduction in fall rate	• Improvement of balance • Group classes delivered by Tai Chi instructors • One-hour class once a week for 16 weeks
Senior Fitness and Prevention (SEFIP) (Kemmler et al., 2010)	46% less likely to fall	• Improvement of flexibility, strength, and aerobic capacity • High intensity group sessions delivered by certified exercise instructors and a home-based exercise routine of increasing difficulty • One-hour group classes and 20-minute home exercise session twice a week during 18 months
Music-Based Multitask Exercise Program (Trombetti et al., 2011)	54% less likely to fall	• Improvement of gait and balance • Group classes consisting of modified Jaques-Dalcroze eurhythmics classes delivered by a certified instructor • Weekly one-hour class during six months
LiFE (Lifestyle Approach to Reducing Falls Trough Exercise) (Clemson et al., 2012)	31% fewer falls	• Integration of balance and strength training exercises into daily activities • In-home sessions with a physical or occupational therapist to add balance and strength strategies in daily activities • Five to seven sessions lasting 40-90 minutes once a week

Table 2.2: Comparison between Fall Prevention Exercise Programmes (Stevens, 2010)

Programme	Reduction in Fall Rates or Risk	Description
Adapted Physical Activity Program (Kovacs et al., 2013)	60% less likely to fall	• Improvement of balance and quality of life • Group classes delivered by physical therapists • One-hour class twice a week for 25 weeks
Multi-target Stepping Program (Yamada et al., 2013)	65% lower fall rate	• Improvement of stepping performance, gait, balance, and control of foot movements • Individual sessions delivered by a physical therapist or exercise instructor in a fitness center for adults • 7 minute sessions twice a week for 24 weeks

2.5.1.1 Otago Exercise Programme

The Otago Exercise Programme was created in the late 1990's in New Zealand specifically to prevent falls by improving muscle strength and balance. The exercises are individually prescribed by a trained instructor and can be performed at home (Campbell and Robertson, 2003). This programme was originally tested in four controlled trials and showed to reduce by 35% both the number of falls and injuries resulting from falls in high-risk older adults (Campbell et al., 1997, 1999; Robertson et al., 2001a,b). Posterior studies also achieved similar results (Shubert et al., 2016; Son et al., 2016; Kyrdalen et al., 2014). This programme comprises a set of five strengthening, twelve balance retraining exercises and a walking plan. A trained instructor should visit the person four or five times to individually prescribe and adapt the exercise plan. The exercise plan increases in difficulty through time by increasing the number of prescribed repetitions, changing the prescribed exercises, and by adding weight in some exercises (when applicable). In the controlled trials, those visits were made at weeks 1, 2, 4 and 8 and another after six months. The exercises take approximately 30 minutes to complete and should be performed three times a week, with rest days in between. The person should also walk up to 30 minutes at least two times a week (Campbell and Robertson, 2003).

The programme starts with 5 minutes of warm-up exercises followed by the strengthening exercises, and the balance exercises described bellow (Campbell and Robertson, 2003).

Strengthening exercises:

1. Front knee strengthening exercise (Figure 2.1): the person attaches a cuff weight to the ankle, sits on a chair, straightens the leg out, and lowers it. After some repetitions, the person should execute the same exercise with the other leg.

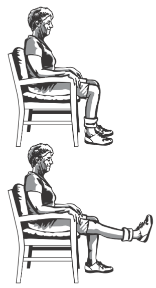


Figure 2.1: Front knee strengthening exercise. Reproduced from Campbell and Robertson (2003)

2. Back knee strengthening exercise (Figure 2.2): standing up and holding on to a stable surface, the person bends the knee, bringing the foot towards his bottom and returns to the starting position. After some repetitions, the same movement is performed with the other leg. Ankle cuff weights are also used in this exercise.

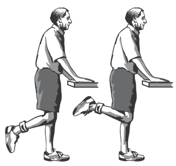


Figure 2.2: Back knee strengthening exercise. Reproduced from Campbell and Robertson (2003)

3. Side hip strengthening exercise (Figure 2.3): standing up and holding on to something stable, the person lifts the leg out to the side and returns to the starting position. After some repetitions, the same movement is executed with the other leg. Ankle cuff weights are also used in this exercise.

Figure 2.3: Back knee strengthening exercise. Reproduced from Campbell and Robertson (2003)

4. Calf raises (Figure 2.4): standing up with the feet shoulder-width apart, the person raises and lowers the heels while the toes stay on the floor, and does some repetitions of the movement. In an initial stage, this exercise can be executed while holding on to a stable surface for support.

(a) (b)

Figure 2.4: Calf raises with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

5. Toe raises (Figure 2.5): standing up with the feet shoulder-width apart, the person raises and lowers the front foot while the heels stay on the floor, and repeats. In an initial phase of the programme, this exercise can also be done with support of a stable surface.

(a) (b)

Figure 2.5: Toe raises with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

Balance retraining exercises:

1. Knee bends (Figure 2.6): starting in standing position with feet placed shoulder-width apart, the person bends the knees and straightens up when the heels start to lift, and repeats. In case of need, the exercise can be executed with support of a stable surface.

(a) (b)

Figure 2.6: Knee bends with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

2. Backwards walking (Figure 2.7): the person walks backwards 10 steps, turns around and walks 10 steps to the beginning. If necessary, the person can hold on to something for support.

(a) (b)

Figure 2.7: Backwards walking with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

3. Walking and turning around (Figure 2.8): the person walks at a regular pace in a figure of eight pattern.

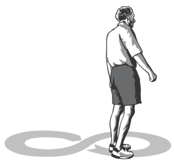


Figure 2.8: Walking and turning around. Reproduced from Campbell and Robertson (2003)

4. Sideways walking (Figure 2.9): the person takes 10 steps to the right, 10 steps to the left and repeats.

Figure 2.9: Sideways walking. Reproduced from Campbell and Robertson (2003)

5. Heel-toe standing (Figure 2.10): the person places one foot directly in front of the other, forming a straight line, and stays in that position for 10 seconds. Afterwards, the front foot is changed and the exercise is repeated. The patient may hold on to a stable surface for support if needed.

(a) (b)

Figure 2.10: Heel toe standing with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

6. Heel-toe walking (tandem walk) (Figure 2.11): the person walks 10 steps placing each foot directly in front of the other, turns around and repeats the exercise. In case of need, the person may hold on to a stable surface for support.

(a) (b)

Figure 2.11: Heel toe walking with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

7. One leg stand (Figure 2.12): the person stands on one leg and tries to maintain that position for 10 seconds. After, the person repeats the exercise standing on the other leg. This exercise can be executed while using support.

(a) (b)

Figure 2.12: One leg stand with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

8. Heel walking (Figure 2.13): the person takes 10 steps walking on heels (with the foot's front off the floor), lowers the feet to the ground, turns around, and walks more 10 steps on heels. If needed, a support can be used.

(a) (b)

Figure 2.13: Heel walking with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

9. Toe walk (Figure 2.14: the person walks 10 steps on toes, lowers the heels to the ground, turns around and walks 10 more steps on his toes. This exercise can be executed while holding on to a stable surface for support.

(a) (b)

Figure 2.14: Toe walk with support (a) and without it (b). Reproduced from Campbell and Robertson (2003)

10. Heel-toe walking backwards (tandem walk backwards) (Figure 2.15): the person takes 10 steps placing each foot directly behind the other, turns around, walks more 10 steps, and repeats the exercise.

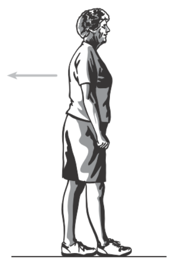
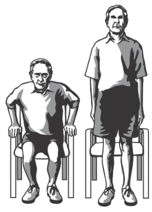
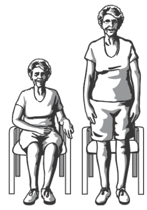


Figure 2.15: Heel toe walking backwards. Reproduced from Campbell and Robertson (2003)

11. Sit to stand (Figure 2.16): the person sits on a chair and then stands ups. The instructor decides the number of hands (two, one or none) that can be used to help the patient to stand up.



(a)



(b)

Figure 2.16: Sit to stand with two hands (a) and with one hand (b). Reproduced from Campbell and Robertson (2003)

12. Stair walking (Figure 2.17): holding on to the handrail, the person goes up and down the stairs. The number of steps on the stairs also depends on the prescription by the instructor.

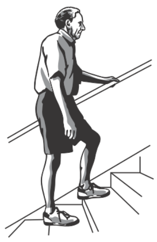


Figure 2.17: Stair walking. Reproduced from Campbell and Robertson (2003)

Chapter 3

Background and Literature Review

Gait analysis is the systematic study of this form of human locomotion. It involves the measurement, description, and assessment of useful quantities to characterise human gait. Research on gait analysis started in the 19th century and has aimed at obtaining objective measurements of different parameters to characterise gait. Gait analysis has been applied in sports, rehabilitation and health diagnostics, and biometric identification (Tao et al., 2012; Muro-de-la Herran et al., 2014; Sprager and Juric, 2015).

In the medical field, gait analysis reveals important information about the progression of diseases such as multiple sclerosis and Parkinson's, rehabilitation results and fall risk. Objective knowledge of gait parameters allows its monitoring and assessment over time, enables early diagnosis of diseases and helps to find the best treatment (Muro-de-la Herran et al., 2014).

3.1 Gait Cycle

Human walking is a periodic movement of the body segments. The gait cycle (GC) consists of stance and swing phases. The stance phase is the phase during which the foot is in contact with the ground. The swing phase is the phase where the foot is not in contact in the ground. Usually, stance phase accounts for 60% of the GC while the remaining 40% of the GC is the swing phase (Bogey, 2016; Tao et al., 2012).

A stride (one GC) is defined as the interval from one event on one limb until the same event on the same limb in the following contact. A step is defined as a portion of the stride from one event occurring on one leg until the same event occurring on the opposite leg. Two steps are a stride. Increasing the walking velocity decreases the duration of the stance phase and the transition to running is marked by the elimination of double support periods (Bogey, 2016; Hamill et al., 2015).

Stance and swing phases can be subdivided into smaller phases. That subdivision varies between authors. Several authors divide a GC into eight phases (Figure 3.1): initial contact, loading response, midstance, terminal stance, pre-swing, initial swing, mid-swing, and terminal swing (Bogey, 2016; Tao et al., 2012). The first four are included in the stance phase, and the swing phase includes the remaining four phases.

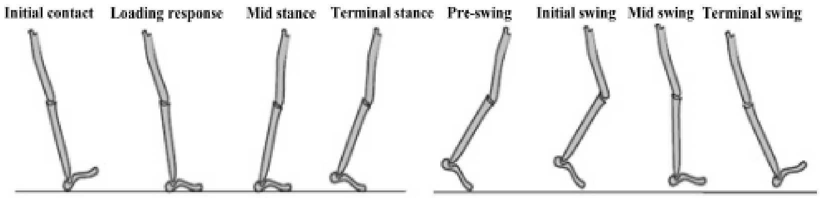


Figure 3.1: Gait phases of a normal gait cycle. Reproduced from Tao et al. (2012).

- **Initial contact** refers to the moment when the foot touches the floor. At this moment, limb's loading response pattern is determined by the joint postures.

- **Loading response phase** is the initial double-stance period. It begins with the initial floor contact and ends when the opposite foot is lifted for swing. During this phase, the knee is flexed to absorb shock and the ankle plantar flexion limits the heel rocker through forefoot contact with the floor.

- **Midstance** is the first half of the single-limb support interval. The limb advances over the stationary foot through ankle dorsiflexion, while the knee and hip extend. This phase begins when the opposite foot is lifted and ends when the body weight is aligned over the forefoot.

- **Terminal stance** completes the single-limb support. It begins when the heel rises and ends when the other foot strikes the floor. During this phase, the body weight moves ahead of the stationary foot.

- **Pre-swing** is the final phase of stance and the second double-stance interval. It comprises the interval between the initial contact of the opposite limb and the ipsilateral toe-off.

- **Initial swing** constitutes, approximately, one-third of the swing period. It begins with a lift of the foot and ends when the swinging foot is opposite to the stance foot. In this phase, the foot is lifted and hip flexion associated with increased knee flexion advance the limb.

- **Mid-swing phase** begins when the swinging limb is opposite to the stance limb and ends when the swinging limb is forward, and the tibia is vertical.

- **Terminal swing phase** begins when the tibia is vertical and ends when the foot strikes the floor. The leg moves ahead the thigh completing limb advancement through knee extension.

All the gait phases have a functional objective, and several pathologies can alter normal gait patterns. Those alterations are different according to the pathologies that caused them (Bogey, 2016).

Table 3.1: Gait parameters (Muro-de-la Herran et al., 2014)

Temporal parameters	• Stride velocity • Cadence or rhythm (number of steps per unit of time) • Step time • Swing time (time interval while each foot is lifted) • Support time (time interval between each foot touching the floor) • Gait autonomy (maximum time interval that a person can walk, taking into account the number and duration of stops) • Duration of stops
Spatial parameters	• Step length (distance between the placements of both feet) • Stride length (distance between consecutive placements of the same foot) • Step width (distance between two equivalent points of both feet) • Step angle (orientation of the foot during step) • Travelled distance • Accumulated altitude/Uneven terrain covered (height difference between drops and rises) • Routes taken • Direction of leg segments • Angles of the different joints (ankle, knee, hip)
Other parameters	• Existence of tremors • Fall record • Gait phases • Ground reaction forces (GRF) • Electrical activity of the muscles (EMG) • Momentum and forces • Body posture

3.2 Gait Parameters

While performing gait analysis, several gait characteristics may be measured. The gait parameters of interest vary according to the research field. Table 3.1 shows gait parameters commonly used in gait analysis (Muro-de-la Herran et al., 2014).

Each person's gait parameters change according to the physical and environmental conditions affecting that person. For example, a person with a limiting physical impairment can adjust to that problem by slowing walking velocity and cadence, increasing the stance phase and decreasing swing phase, and shortening stride length (Hamill et al., 2015).

Gait analysis may be used to help distinguish between different health issues because different pathologies cause different gait disorders. For example, Alzheimer's disease, the most common cause of dementia, and vascular dementia both cause gait disorders but in different stages of the disease (Axer et al., 2010). Patients with Alzheimer's disease walk slower, have a smaller step length and a higher variability between steps. These disorders appear in a later stage of the disease than in vascular dementia. Vascular dementia patients show smaller step length, wide-based gait, rigidity, disturbance of postural control, freezing of gait, disturbance in the initiation of gait and gait apraxia (the patient walks with a broad-based gait, taking short steps and placing the feet flat on the ground). Parkinson's disease also causes gait disturbances such as smaller step length and frequency. Freezing of gait is another gait disturbance in Parkinson's disease patients in which the person is unable to continue walking (Axer et al., 2010).

3.3 Gait Analysis Techniques

Gait analysis can be performed using different methods. They are chosen based on clinical needs, financial considerations and available resources. Traditional methods are based on observations made by medical staff, but these methods give mostly subjective measurements or simple low-accuracy objective ones. Technology advancements allowed the creation and development of new techniques to obtain more objective measurements (Muro-de-la Herran et al., 2014).

3.3.1 Observation-based analysis techniques

Observation-based methods usually consist of analyses carried out in clinical conditions by a specialist that evaluates the gait parameters by observing the patient walking in a pre-determined circuit (Muro-de-la Herran et al., 2014). Commonly used techniques include:

- **Timed 25-Foot Walk (T25-FW):** the patient is instructed to walk 25-foot (7.62 metres) as fast and safely as possible in a straight line and is timed while doing it. The patient may use assistive gait devices during the test. This technique is practical, requires minimal equipment and space, and it is commonly used in the assessment of walking disability in multiple sclerosis patients (Motl et al., 2017);

- **Multiple Sclerosis Walking Scale (MSWS-12):** self-assessment scale in which 12 parameters regarding walking difficulties are assessed. It was created for multiple sclerosis patients, and a modified version called Walk-12 is also clinically useful in other pathologies (Holland et al., 2006);

- **Tinetti Performance-Oriented Mobility Assessment (POMA):** it is a test that identifies impairments in various components of gait and balance. It has 16 parameters evaluated by a specialist who observes the patient while doing several exercises such as rising from a chair and walk 10 feet (3.05 metres) and returning to the starting point (Abbruzzese, 1998);

- **Timed Get up and Go (TUG):** the patient is timed while getting up from a sitting position, walking a short distance, turning around, walking back to the chair and sitting down again (Mathias et al., 1986);

- **Gait Abnormality Rating Scale (GARS):** the patient walks a 10-metres distance and returns to the starting point while being recorded. Afterwards, the videos are watched by specialists that assign scores to 16 parameters. Five of them are general characteristics, four are related to the lower limbs, and the remaining seven evaluate trunk, head and upper limbs characteristics (Wolfson et al., 1990);

- **Extra-Laboratory Gait Assessment Method (ELGAM):** the patient walks a 5-metre distance several times to measure the following characteristics: step length, speed, initial gait style (slow or energetic), ability to turn the head and static balance. This method can be applied in the home of the patient, but it still requires a specialist to evaluate all the parameters (Fried et al., 1990).

3.3.2 Objective analysis techniques

Objective analysis techniques measure gait parameters accurately helping healthcare professionals to diagnose gait disorders better, decide their treatment and evaluate patients' improvements over time.

3.3.2.1 Video-based motion capture systems

The first objective techniques were video-based motion capture systems. Currently, these systems are the gold standard in gait analysis (Tao et al., 2012). They usually include several cameras that record a person walking from different angles by means of markers attached to the person in specific locations such as joints. By tracking the dynamic position of those markers during the recorded time, gait waveforms are obtained and walking features extracted (Lei et al., 2014). The use of markers is one of the disadvantages of these systems because their placement is time-consuming and they may be uncomfortable, even restricting or inhibiting the movement. For this reason, some markerless techniques have already been presented (Vishnoi et al., 2014; Sandau et al., 2014).

These techniques allow three-dimensional analysis and sub-millimetre accuracy. However, video-based motion capture systems still need specialised laboratories with expensive equipment and trained personnel, and need a lengthy set-up and post-processing. Moreover, there are also limitations in the moving area inside the laboratory, and the immobility of the system prevents most of the continuous longitudinal monitoring situations (Tao et al., 2012; Chen et al., 2011).

3.3.2.2 Force and pressure sensors

Force sensors measure the force interactions with the floor while walking. Usually, they have the shape of a plate to walkover. This force is known as ground reaction force (GRF) and is a three-dimensional (3D) vector describing the force components in the three directions (Muro-de-la Herran et al., 2014). These sensors are particularly useful in detecting gait events, such as the start and the end of the stance phase, and can be used in association with other sensory systems, such as inertial sensors (Aoike et al., 2016; Bamberg et al., 2008). Pressure measurement systems are similar to force sensors and quantify the pressure patterns under a foot over time but cannot quantify horizontal or shear components of the applied forces (Muro-de-la Herran et al., 2014).

Both these sensors only provide information when the person walks on them what may alter normal gait in an effort to step on the sensor (Muro-de-la Herran et al., 2014). That problem can be overcome if the sensors are incorporated in treadmills or footwear as in Bamberg et al. (2008), Liu et al. (2010) and Day et al. (2012). Incorporation of sensors in footwear also allows data collection throughout the day and in a variety of environments. When using treadmills with sensors incorporated, subject preparation is almost unnecessary, but those still are expensive equipments that requires a specialised laboratory. Furthermore, both force and pressure sensors can only assess gait parameters related to ground contact, i.e. joint angles outside the ground plane cannot be tracked (Rampp et al., 2015).

3.3.2.3 Electromyography

Electromyography (EMG) measures the electrical activity of the muscles. The EMG signal provides information concerning the control of voluntary and reflexive movements and is useful to understand gait disorders and the muscles involved (Hamill et al., 2015). Since the muscle activity occurs in a repetitive manner during the gait cycle, EMG signals from several muscle positions can also be used to detect different gait phases (Taborri et al., 2016; Strazza et al., 2017). EMG signals can be non-invasively measured with surface electrodes or invasively with indwelling electrodes. Surface electrodes are placed on top of the skin and are mainly used for superficial muscles. Indwelling electrodes may be either a needle or a fine wire placed directly in the muscle, and are used for deep or small muscles (Hamill et al., 2015).

The magnitude of EMG signals is very small (in the order of $10\mu V$ to $5mV$) and represents the electric activity of multiple motor units in the proximity of the sensor electrodes. In consequence, the correct placement of these electrodes is critical to obtain a good record; however the magnitude of the signal may not be directly proportional to the tension created in the observed muscle. Additionally, the use of this method faces challenges such as a significant complexity in the signal acquisition and post-processing (Muro-de-la Herran et al., 2014; Tao et al., 2012; Hamill et al., 2015).

3.3.2.4 Inertial sensors

Inertial sensors measure their own movement using the inertia principle. Accelerometers and gyroscopes are examples of inertial sensors, and an IMU is a device that incorporates accelerometers, gyroscopes and, optionally, magnetometers (Iosa et al., 2016). These sensors are commercially available in small, light-weight units that may be embedded with Bluetooth/wireless transmitters or memory cards. This makes them able to be easily fixed to a body segment without restraining movement and to perform gait analysis outside a laboratory environment (Iosa et al., 2016). These sensors require little subject preparation and enable estimation of three-dimensional gait parameters. Therefore, these sensors can be part of wearable devices able to collect important free-living physiological signals of patients, so facilitating remote monitoring.

Accelerometers measure the external specific force acting on the sensor. That force consists in the sensor's acceleration and earth's gravity (Kok et al., 2017). Generally, their principle of operation is based on a mechanical sensing element comprising a proof mass attached to a mechanical suspension system. The acceleration can be related to the reluctance of the mass to move when it is driven by an external force (Iosa et al., 2016; Tao et al., 2012). Accelerometer measurements can be affected by bias which is the offset of its output value relative to the real value. Accelerometer bias can be estimated by measuring the long-term average of the accelerometer's output when it is not undergoing any acceleration (Ayub et al., 2012).

Gyroscopes measure angular velocity and are based on the Coriolis effect. Coriolis force is an apparent force proportional to the angular rate of rotation in a rotating reference frame. By detecting the linear motion from the Coriolis effort and performing integration of the gyroscopic signal, the angular rate can be obtained (Tao et al., 2012). Gyroscopes can be used to obtain the orientation of the sensor while in motion. However, gyroscope measurements are also affected by bias and numerical errors. Bias influence is noticed after integration as it causes an angular drift that increases linearly over time. Another issue that appears when using gyroscopes is the calibration error which refers to errors in the scale factors, alignments, and linearity of the gyroscopes. Those errors are only observed while the sensor is turning, and lead to the accumulation of additional drift in the integrated signal (Ayub et al., 2012).

Magnetometers measure the magnetic field along a sensitive axis and are based on the magnetoresistive effect. This effect relates to changes in the resistivity of a current carrying ferromagnetic material resulting from a magnetic field. Those resistance changes are proportional to the tilt angle in relation to the magnetic field direction. Magnetometers can estimate changes in orientation in relation to the magnetic North or another axis (Tao et al., 2012). However, magnetic interference in the surrounding environment and in the device itself can cause measurement errors (Ayub et al., 2012).

Accelerometers, gyroscopes and magnetometers can be built to have one, two or three sensitive axis allowing measurements in one, two or three directions, respectively. Although it is possible to perform gait analysis using only one type of these sensors, as in Bouten et al. (1997) and Tunçel et al. (2009), they can also be used simultaneously to overcome sensors' weaknesses such as the magnetic interference that affects magnetometers.

The accurate estimation of gait parameters using IMUs, a crucial aspect of medical systems, is still an open field of research as there are still many difficulties to overcome. Moreover, techniques to translate inertial sensor signals to more easily interpretable data are still complex, intrinsic integration noise causes integration drift, the uncertainty of mounting nodes on the human body is responsible for a systematic bias, and movement in multiple planes can cause computational errors (Godfrey, 2017; Chen et al., 2011). When using IMUs, they need to be rigidly fixed to the body segment, in order to avoid motion artefacts, because they measure acceleration, angular velocity and magnetic field with respect to the axes of a sensor-embedded system of reference. Ideally, the sensor's axes should be aligned with the anatomic axes of the body segments, and the same orientation between different trials should be kept because the same signal is captured differently by the same sensor if the orientation changes (Fong and Chan, 2010; Ngo et al., 2015). This issue deserved the attention of several authors that presented methods to tackle this challenge. One possible approach is employing a one-dimension orientation-invariant signal as the magnitude of a 3D signal from an accelerometer or gyroscope, but, in that case, information of the orientation is lost (Siirtola and Röning, 2012). In the work of Ngo et al. (2015), a sensor orientation-compensative matching algorithm is used with two sensor orientation invariants: the magnitude of the 3D signal and the earth's gravity force. Other common approach is to estimate the orientation of the device in relation to a fixed frame at each instant (Iosa et al., 2016).

3.4 Gait Analysis in Functional Walking Exercises

Several techniques for gait analysis already exist. However, most of them are only used in free walking exercises and are not able to analyse more challenging exercises such as the ones from the Otago Exercise Programme. Even though, some examples of analysis of those type of exercises can be found in the literature and are described below.

In order to analyse the kinematic characteristics on a horizontal plane, when walking with a tandem gait on a sine wave walkway, Kawakami et al. (2016) used a six-camera, three-dimensional motion analysis system. The recorded data was used to calculate the trunk, hip joint, and knee joint rotation angles and it was concluded that the rotation of the knee joint was important during changes of direction.

In the work of Lee et al. (2013), a motion capture system and force plates were used to acquire joint movements and GRFs. Then, joint moments and powers were calculated during forward and backwards walking. They found that, in backwards walking, the ankle joint was the main responsible for propulsion and shock absorption. From the comparison of the gait in the two directions, it was found that the characteristics of angular displacement in all joints were almost identical in forward walking and time-reverse backwards walking. However, some crucial points of joint angles presented significant differences. Another finding was that the range of motion in all joints was significantly smaller in backwards walking. The moment pattern of the ankle joint was similar in forward walking and in time-reversed backwards walking but, in the knee and hip joints, the moment pattern was simpler in time-reversed backwards walking. All joints showed differences in the power patterns for the two movements.

In the work of Day et al. (2012), balance in post-spinal cord injury patients was evaluated using a twelve camera system together with three-dimensional GRFs. Walking balance was evaluated trough variability in spatial parameters, foot placement relative to the centre-of-mass and a measure called margin of stability. This later compares the shortest mediolateral distance between the centre-of-pressure (CoP) and a vertical projection of the centre-of-mass in the direction of its velocity. The spatial parameters used were step width, step length, mediolateral foot placement, and anteroposterior foot placement.

The work of Cohen et al. (2013) evaluated people with peripheral neuropathies while performing the Tandem Walking Test. Their method used kinematic data from a torso-mounted IMU to count the maximum number of correct consecutive steps each subject performed. The steps were considered incorrect if the person took a side step or made a space between the feet.

Toe-walking is a gait disturbance often observed in children with cerebral palsy and Mancinelli et al. (2009) presented a method to assess the severity of toe-walking based on the trajectory of the CoP and the kinematics of the ankle. In their study, they used an 8-camera motion capture system to extract the kinematic characteristics of the movement, and two force platforms to estimate the trajectories of the CoP. Chen et al. (2011) studied the use of IMUs to assess the efficacy of ankle-foot orthoses in longitudinal studies. To achieve that goal, they used one IMU placed on the lateral side of the shank and another on top of the foot to measure the ankle joint angle.

Cadenas-Sánchez et al. (2016) compared spatiotemporal characteristics and joint angles during forward and backwards walking in water at low and high frequencies. Data were collected with eight young adults that were recorded using four cameras. The computed spatiotemporal parameters were speed, stride length, step length, support phase duration and step length asymmetry. Ankle, knee and hip joint angles were also computed at initial contact and final stance. Speed, stride length and step length were smaller in backwards walking. Support phase duration was lower at backwards walking. At initial contact, ankle and hip joint were less flexed during backwards walking, and the knee joint showed more flexion at forward walking.

3.5 State-of-the-art in Gait Analysis Stages

As described in the previous section, examples of gait analysis in functional exercises are scarce. Nevertheless, the analysis of any gait exercise has similar stages (i.e. stride detection), and the algorithms used in forward gait can be modified to be used with other exercises. Therefore, the following sections present the state-of-the-art in stride segmentation, turning detection, stride length estimation, trajectory estimation, gait symmetry assessment, and also orientation representation and estimation.

3.5.1 Stride Segmentation

Gait is a periodic movement, and that characteristic can be used to detect strides. Several approaches have already been proposed to detect steps and segment them into several gait phases. Those approaches depend on the selected sensor and its placement on the human body. The most common methods can be divided into four groups: approaches based on signal's characteristics, wavelet-based methods, dynamic time warping (DTW) and Hidden Markov Models (HMM).

Approaches based on the signal's characteristics use the knowledge about the signals patterns to detect strides and segment them into several gait phases. The cyclical pattern of the angular velocity in the sagittal plane has been used by several authors to detect strides and gait events such as toe-off and heel-strike in different populations (Meng et al., 2013; Salarian et al., 2004; Yang et al., 2013; Catalfamo et al., 2010; Lee et al., 2010; Lee and Park, 2011). In Rebula et al. (2013), thresholds are used on the magnitude of acceleration and angular velocity signals to identify stationary periods in strides. In Wang et al. (2013), Silva et al. (2017) and Ruppelt et al. (2016), it was possible to segment each stride into five gait phases. These approaches are also called finite-state-machines (FSM). Due to the cyclical nature of gait, they are simple to apply, and can accurately identify several gait phases. However, their accuracy could lower in impaired populations that may not exhibit all the normal gait phases and show an abnormal signal pattern (Park and Suh, 2010; Pappas et al., 2001).

Wavelet-based methods use wavelet transforms to decompose the acceleration or the angular velocity into different frequency components and detect events such as heel-strike (Kose et al., 2011; Aminian et al., 2002; Gouwanda and Senanayake, 2009; Khandelwal and Wickström, 2014).

Template-based cross-correlation methods and Dynamic Time Warping (DTW) find the similarity between a template and a time sequence to detect strides (Rampp et al., 2015; Barth et al., 2015; Ying et al., 2007). However, these approaches require the use of a pre-defined template.

HMM are a machine learning method used for modelling sequences of data. These methods work on representing probability distributions over sequences of strides, and were already used to segment strides in pathological and healthy populations (Mannini et al., 2015; Haji Ghassemi et al., 2018; Taborri et al., 2014).

3.5.2 Turning Detection

Detection of turns during gait is another aspect that has not received enough attention from researchers. The proposed approaches to detect turns are based on thresholds.

In the works of Mariani et al. (2010), Mariani et al. (2013) and Pham et al. (2017), turns were detected based on the variation of the IMU's orientation around the vertical axis between the beginning and the end of each gait cycle.

In the work of El-Gohary et al. (2014), turns were detected based on the angular velocity around the vertical axis and the rotation angle around that same axis.

A combination of the two previous methods was proposed by Novak et al. (2014) to overcome each method's weaknesses in a real-time application. In their work, turns were initially detected when the angular velocity was higher than a threshold value. In order to avoid missing smaller or slower turns, turns could also be detected later when the device's orientation had sufficiently changed.

3.5.3 Stride Length and Trajectory Estimation

Stride length estimation is a widely explored subject due to its utility in several applications such as pedestrian navigation, gait analysis, rehabilitation, and sports training. Stride length estimation methods can be divided into four groups: biomechanical model based approaches, empirical models, machine learning approaches and double-integration approaches.

Biomechanical model based approaches model the lower limbs as a double pendulum during swing phase and an inverted pendulum during the stance phase. Stride length is then obtained as a function of the leg length and the angle described by the forward swing of the leg (Wu et al., 2015). These methods limit the movement to the sagittal plane, therefore preventing their application to trajectory estimation. Moreover, specific subject characteristics such as the leg length or the distance between the sensor and the ankle joint are needed to scale the models (Wu et al., 2015; Silva et al., 2017; Zhao et al., 2017).

Empirical models use linear or non-linear relationships between stride length and measured parameters, such as walking frequency (Shin et al., 2007; Zhao et al., 2017). Stride length is calculated with simple equations, such as equation 3.1 presented by Shin et al. (2007) where f is the walking frequency, v is the walking velocity, and α, β and γ are pre-calibrated parameters. However, these approaches require training data to estimate the parameters which are different for each person.

$$SL = \alpha \cdot f + \beta \cdot v + \gamma \tag{3.1}$$

Methods using machine learning techniques are still rare, but recently, Hannink et al. (2016) used deep convolutional neural networks to map stride-to-stride inertial data to the stride length and achieved an average accuracy of 0.01+/-5.37 centimetres on a public dataset of geriatric patients.

In double-integration approaches, the acceleration signal in sensor coordinates is transformed into world coordinates (this transformation will be explained in section 3.5.5), the gravity component is removed, and the stride length is the result of the double integration of the acceleration signal. Using these methods, it is possible to obtain the displacement in three directions and, consequently, estimate the trajectory and position of the subject. However, these methods' accuracy is highly dependent on a correct orientation estimation and the minimisation of integration drift (Rampp et al., 2015; Wang et al., 2013).

Integration drift is caused by intrinsic measurement errors in the currently available sensors. Those errors have a quadratic effect on the result after double integration. In order to minimise integration drift, it is possible to model the expected error during sensor utilisation and correct sensor readings or combine inertial sensors with others that have lower sampling rates but do not drift over time, such as global navigation satellite systems (GNSS) (Kok et al., 2017). Another common approach is to enforce several constraints such as zero velocity at the end and at the start of the stride which is a technique also known as zero velocity updates (ZUPT). This technique is mainly used when the sensors are placed in the feet, but similar approaches can also be applied when the sensors are placed in the ankles or shanks (Bishop and Li, 2010; Silva et al., 2017; Sijobert et al., 2015; Yang et al., 2013; Wang et al., 2013). When using the sensors in the ankle or shank, the periods of inactivity may be smaller or even non-existent. In the work of Wang et al. (2013), sensors were placed on the ankle, and a ZUPT technique was also applied. In the work of Yang et al. (2013), the sensors were on the shank and the shank vertical event was used as the starting and ending point in each stride to correct velocity estimation. When the shank was vertical, the velocity was minimal, and could be calculated with equation 3.2, where $v(T)$ is the linear velocity at time T, $w(T)$ is the angular velocity measured with the sensor at time T, and L is the distance between the sensor and the ankle joint. This velocity value is then used as a reference to correct velocity estimation.

$$v(T) = w(T) \cdot L \tag{3.2}$$

Although integration is usually done directly, i.e. forward in time, Trojaniello et al. (2014) proposes a direct and indirect integration scheme where each stride is integrated twice and a weighted mean is computed with weights depending on the distance to the next ZUPT.

3.5.4 Gait Symmetry Assessment

Gait is a complex act that requires the periodic interaction between multiple body segments. Therefore, it is predictable that physiological changes, such as ageing and neurodegenerative diseases, can compromise the gait function. Gait asymmetry or the lack of symmetry refers to the amount of divergence between the left and right side of the body. Even considering that, in a healthy individual, gait is symmetrical with minor deviations between the dominant and non-dominant leg (Sadeghi, 2003), assessing gait symmetry appears to be relevant when differentiating between normal and pathological gait. In addition to being a manifestation of a disease, gait asymmetry may lead to other complications. Asymmetric gait is not efficient because it increases oxygen consumption and energy cost of locomotion (da Cunha-Filho et al., 2003). The impaired limb may lose bone mass density leading to osteoporosis (Jørgensen et al., 2000). The opposite limb has an increased risk of osteoarthritis and musculoskeletal injury due to the higher dynamic load (Block and Shakoor, 2010). Gait asymmetry may be used to distinguish between a healthy and an impaired individual, but also to distinguish what stage in a disease a patient is and assess the results of rehabilitation (Wafai et al., 2015; Yu et al., 2015; Sant'Anna et al., 2011).

Despite the clinical importance of gait symmetry, there is not yet a standardized approach to its assessment. According to the work of Viteckova et al. (2018), the current methods to evaluate asymmetry in gait can be divided into four groups: discrete approaches, complete gait cycle approaches, statistical approaches, and non-linear approaches.

Discrete approaches are the most commonly used method as they are simple and easy to interpret. Symmetry is calculated using simple equations and gait features, the methods differing on the chosen equations and gait variables. Spatiotemporal characteristics such as step length, step time, duration of stance or swing gait phase are the most commonly used variables. In equations 3.3, 3.4 and 3.5, the ratio index (RI) (Seliktar and Mizrahi, 1986), the Robinson index also known as symmetry index (SI) (Robinson et al., 1987), and the symmetry angle (SA) (Zifchock et al., 2008) are presented as examples.

$$RI = \frac{X_1}{X_2} \tag{3.3}$$

$$SI = \frac{2 \cdot (X_u - X_a)}{X_u + X_a} \cdot 100 \tag{3.4}$$

$$SA = \frac{\arctan(\frac{X_a}{X_u}) \cdot 100}{90} \tag{3.5}$$

In equation 3.3, X_1 and X_2 represent each limb's value for the used variable. Perfect gait symmetry is achieved when the value of RI equals one, and any other higher or lower value indicates an asymmetric gait. This index has some limitations, such as not presenting an upper limitation of the result, and the fact that RI value depends on whether the greater values are used as the numerator or the denominator (Viteckova et al., 2018).

In both equations 3.4 and 3.5, X_u represents the unaffected limb's variable value, and X_a is the affected limb's variable value. According to Robinson's index, the value of perfect symmetry is zero, and any other value means some asymmetry. The limitations of this index include the unlimited lower and upper bounds of the index, the need to be normalised to a reference value, and the fact that it is variable specific which means that it is not valid to use one simple criterion value to assess gait symmetry when using several gait variables (Herzog et al., 1989; Zifchock et al., 2008). To overcome the disadvantages of Robinson's index, Zifchock et al. (2008) proposed the use of the symmetry angle.

Discrete approaches are simple and easy to interpret, however, they are not able to capture the complexity of the movement as they are calculated based on a single discrete value over the entire movement. These methods do not take into account the temporal information in gait waveforms and the extraction of the discrete variables, such as step length, are subject to errors.

Complete gait cycle approaches, such as trend symmetry, cyclogram-based method, region-of-deviations, and symbol-based method, can overcome this disadvantage.

Trend symmetry is a method proposed by Crenshaw and Richards (2006) to analyse joint angle symmetry and normality. This approach uses eigenvectors to compare the waveforms from both left and right limbs and can identify asymmetric joint behaviour. However, it is not possible to identify the timing a which the difference between limbs occurs in the gait cycle.

A cyclogram-based method to identify gait asymmetry was first used by Goswami (2003). Cyclograms are diagrams generated by plotting simultaneously two variables. Gait symmetry is quantified using the geometric properties of a cyclogram representing the same gait variables from the two limbs. In this method, perfect symmetry is represented by the value zero. However, there is no upper limit for the level of asymmetry.

Region of deviations is a method proposed by Shorter et al. (2008) to assess asymmetry behaviour of joint angles. This approach computes the difference between the angle of the same joint in each limb over several gait cycles. The average difference is then compared to joint motion data of healthy subjects. However, one limitation of this method is the fact that it needs additional subjects and experiences in order to obtain data to be used as a reference.

The work of Sant'Anna et al. (2011), proposed a new method based on a symbolic representation of the original signal. The acquired signal is partitioned into ten different quantisation values, and the values between consecutive partitions are represented by a symbol. The symmetry value is obtained by comparing the histograms of the right and left signals and varies between 0 (perfect symmetry) and 100. One shortcoming of this method is that it depends on the definition of the number of partitions (Sant'Anna et al., 2011).

Statistical methods include cross-correlation, autocorrelation, principal components analysis (PCA), and root-mean-square values for continuous signals, and discrete parameters may be analysed by ANOVA and the *t*-test. These approaches may overcome some of the limitations of the previous methods, but their computation is more complex, and their interpretation is not as clear as discrete approaches (Viteckova et al., 2018).

Non-linear approaches, such as multi-resolution entropy and cross-fuzzy entropy, use direct variables extracted from continuous signals and evaluate their evolution through several gait cycles. The main disadvantage of these methods is the need to set up some parameters before utilisation (Viteckova et al., 2018).

3.5.5 Orientation Representation and Estimation

As data provided by the sensors of an IMU are measured according to the sensor's axes, most IMU applications in gait analysis need information about the device's orientation at any time. Knowing the orientation of the sensor in relation to other coordinate frame is helpful to overcome issues related to uncertainty in the placement of the sensors and also to estimate some gait parameters, such as stride length (Iosa et al., 2016). For example, using an IMU attached to the shank, the z-axis may start aligned with the vertical direction and the leg but, throughout the gait, that axis will always be aligned with the leg but not with the vertical direction. Therefore, to obtain the stride length in one direction, it is not possible to just double integrate the acceleration measured in one of the accelerometer's axes, because that axis is not always aligned with the chosen direction.

An IMU's orientation is usually defined in relation to a fixed frame. Three commonly used coordinate frames are described bellow.

- The sensor frame, s, also known as body frame, is the coordinate frame of the IMU. Usually, its origin is located in the centre of the device and it is aligned to the devices' casing. All the IMU measurements are given in this frame (Kok et al., 2017).
- The earth frame, e, is a static frame. Its origin is located at the centre of the earth and it is attached to the centre of the earth. Therefore, the x-axis points north, y-axis points east and z-axis points toward the centre of the earth (Kok et al., 2017).
- The world frame, w, is another static frame that can be used as an alternative to the earth frame. In this case, the frame is fixed at a known location in space, and the axes do not necessarily point north, east and to the centre of the earth (Sprague, 2016).

By knowing the orientation of the IMU with respect to a reference frame, it is possible to transform coordinates from one frame to another. The orientation, also known as angular position or attitude, can be represented using the rotation matrices, rotation vector, Euler angles and quaternions (Sprague, 2016).

3.5.5.1 Rotation matrices

Rotation matrices, R, are unique descriptions of the orientation with the following properties:

$$RR^T = R^T R = I_3 \ , \ det\ R = 1 \tag{3.6}$$

Considering two coordinates frames u and v, a vector x expressed in the u-frame can be transformed into the v-frame using equation 3.7. The inverse transformation can be performed according to equation 3.8 (Kok et al., 2017).

$$x^u = R^{uv} x^v \tag{3.7}$$

$$x^v = (R^{uv})^T x^u = R^{vu} x^u \tag{3.8}$$

3.5.5.2 Rotation vector

The rotation between two coordinate frames can also be expressed in terms of an angle α and a unit vector n around which the rotation takes place. Using this representation, the rotation of vector x from the v-frame into the u-frame is computed using equation 3.9 (Kok et al., 2017).

$$x^u = x^v cos\alpha + n^v (x^v \cdot n^v)(1 - cos\alpha) - (n^v \times x^v) sin\alpha \tag{3.9}$$

The rotation vector representation is not unique because adding 2π to any angle α results in the same orientation (Kok et al., 2017).

3.5.5.3 Euler angles

Euler angles are an intuitive representation of the orientation that is expressed as a sequence of three rotations around the three coordinate axes. Those rotations are usually called roll, pitch and yaw (or heading), Figure 3.2. Pitch and roll angles together are often referred to as inclination (Sprague, 2016; Kok et al., 2017).

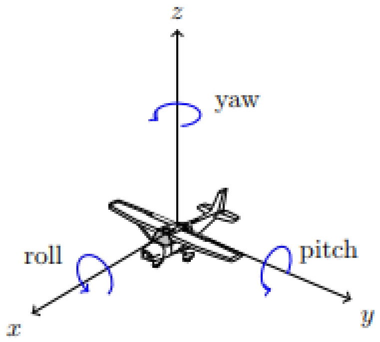


Figure 3.2: Euler angles. Reproduced from (Sprague, 2016).

Assuming that the v-frame is rotated an angle ψ around the z-axis, an angle θ around the y-axis and an angle ϕ around the x-axis, the rotation matrix R^{uv} is represented in equation 3.10 where e_1, e_2 and e_3 are the unit vectors defined in 3.11.

$$\begin{aligned} R^{uv} = & \; R^{uv}(e_1,\phi)R^{uv}(e_2,\theta)R^{uv}(e_3,\psi) \\ = & \begin{pmatrix} 1 & 0 & 0 \\ 0 & cos\phi & sin\phi \\ 0 & -sin\phi & cos\phi \end{pmatrix} \begin{pmatrix} cos\theta & 0 & -sin\theta \\ 0 & 1 & 0 \\ sin\theta & 0 & cos\theta \end{pmatrix} \begin{pmatrix} cos\psi & sin\psi & 0 \\ -sin\psi & cos\psi & 0 \\ 0 & 0 & 1 \end{pmatrix} \end{aligned} \tag{3.10}$$

$$e_1 = (1\;0\;0)^T, \;\; e_2 = (0\;1\;0)^T, \;\; e_3 = (0\;0\;1)^T \tag{3.11}$$

When working with this representation it is necessary to specify the order in which the rotations are applied, and the main disadvantage is the existence of singularities which make the mapping from spatial orientations to Euler angles discontinuous (i.e. small changes in orientation may cause big jumps in the required representation) (Sprague, 2016).

3.5.5.4 Unit quaternions

A quaternion is a four-dimensional complex number that can be used to represent orientation. A quaternion can be represented using Equation 3.12.

$$q = (q_0\;q_1\;q_2\;q_3)^T = \begin{pmatrix} q_0 \\ q_v \end{pmatrix} \tag{3.12}$$

A rotation from v-frame into u-frame can be defined as

$$\bar{x}^u = q^{uv} \odot \bar{x}^v \odot (q^{uv})^c \tag{3.13}$$

where $.^C$ denotes the quaternion conjugate, defined as

$$q^c = (q_0 \;\; - q_v^T)^T \tag{3.14}$$

and $\bar{x}^v$ denotes the quaternion representation of x^v as

$$\bar{x}^v = (0 \;\; (x^v)^T)^T \tag{3.15}$$

The notation $\odot$ denotes the quaternion multiplication defined as

$$p \odot q = \begin{pmatrix} p_0 q_0 - p_v \cdot q_v \\ p_0 q_v + q_0 p_v + p_v \times q_v \end{pmatrix} \tag{3.16}$$

A quaternion must have unity norm to represent rotation. One ambiguity is that a unit quaternion is not a unique representation of orientation because q and $-q$ represent the same orientation, however this representation has no singularities. An additional problem is that the four quaternion parameters do not have intuitive physical meanings (Sprague, 2016; Kok et al., 2017).

3.5.5.5 Orientation estimation

The orientation is many times estimated using sensor fusion techniques. The most common techniques to estimate orientation uses Kalman filters or complementary filters. Both approaches are shown to allow an acceptable estimation of orientation based on noisy and biased measurements from different sensors like accelerometers and gyroscopes (Perez et al., 2011).

Kalman filters calculate the best estimate of the state of a dynamic system from noisy measurements by minimising the mean squared error of the estimate. It is implemented in two stages: prediction and correction. The optimal performance of this filter is obtained when the noise sources are independent Gaussian processes with zero mean and the system dynamics is linear (Perez et al., 2011). In non-linear systems, an extended Kalman filter can be used (Sabatini, 2006).

The complementary filter is a more straightforward, intuitive and less computationally demanding approach to estimate orientation. The accelerometer can provide an orientation estimation in a static state when it is only measuring the earth's gravity, so it is reliable only on the long term. The gyroscope can provide an orientation estimation that is only reliable on the short term, because the orientation is estimated by integrating the gyroscope's measurements, which starts to drift over time. So, to estimate the orientation, the complementary filter blends static information provided by the accelerometers and magnetometers with dynamic information provided by the gyroscopes (Calusdian et al., 2011).

Chapter 4

Methodology

The gait analysis methodologies proposed in the literature are always adjusted to the goal of those works, so there is not a standardised methodology to follow. In this work, two IMUs were used to collect data in order to analyse functional gait exercises. The exercises were selected from the Otago Exercise Programme, and gait parameters of interest were defined. The gait analysis methodology used to assess the exercises was divided into several stages: stride segmentation, turning detection, stride length and trajectory estimation, shank-to-vertical angle estimation and gait symmetry assessment. Later, this methodology was validated with data collected from two groups of participants.

The following sections present a more detailed explanation of the used methodology to assess the exercises and its validation.

4.1 Data acquisition

4.1.1 Sensors

In this work, two wearable devices were used, namely Pandlets. Pandlets were developed at Fraunhofer AICOS and included an IMU constituted by a 3-axis accelerometer, a 3-axis gyroscope and a 3-axis magnetometer. Besides the readings of these three sensors, Pandlets also provided sensor orientation signals in the quaternion form. The orientation signal was estimated with a 2^{nd} order complementary filter applied to accelerometer and gyroscope signals.

Figure 4.1 shows a Pandlet and the Velcro straps used to secure it to the chosen location. Its diameter is 45 millimetres and its height is 15 millimetres.

For the data acquisition, both IMUs were connected to a computer via Bluetooth. Data were recorded using the PhysioModel, which is an application developed at Fraunhofer AICOS, and exported into a *.csv* file. Accelerometer and gyroscope signals were sampled at 50 Hz.

Figure 4.1: Pandlet developed at Fraunhofer AICOS.

4.1.2 Sensor placement

Currently, there is not yet an agreement regarding the best location to place the sensors or the number of sensors to use. Usually, those details are chosen according to the goal of the study. In the literature, the number of sensors varies between one and seven sensors (Tadano et al., 2013; Takeda et al., 2009; Kose et al., 2011). Regarding sensor placement, common locations include trunk (Zijlstra and Hof, 2003), waist (Kose et al., 2011), thighs (Taborri et al., 2014), shanks (Sijobert et al., 2015), ankles (Wang et al., 2013), and feet (Park and Suh, 2010).

By placing one IMU in each limb, it would be possible to obtain information regarding both limbs and evaluate differences between them; therefore the possible locations were thighs, shanks and feet. In general, gait events are easier to identify when the sensor is placed in a location near to the contact point, so better results are expected when placing IMUs on the shank or foot (Trojaniello et al., 2014; Storm et al., 2016). Between those locations, the shank presents several advantages: it is a more rigid segment that allows a firmer attachment of the device; the recorded signals are less variable between subjects when compared to foot signals; and no specific footwear or footwear adaptations are needed (Trojaniello et al., 2014; Catalfamo et al., 2010).

In this work, each Pandlet was placed on the lateral side of each shank, above the ankle joint as presented in Figure 4.2a. Both IMUs were placed in the same orientation in both limbs, Figure 4.2b. The x-axis was in the vertical direction and pointed up; the y-axis was in the direction of the movement and pointed forward, and the z-axis was perpendicular to the sagittal plane and pointed to the subject's left.

4.2 Gait Parameters

Different gait analysis applications have different parameters of interest. In this work, gait parameters of interest include the number of strides and the duration of each one, stride length, trajectory, velocity, cadence, and also their respective variabilities. Gait parameters variability is associated with ageing, mobility and balance impairments (Callisaya et al., 2010; Hausdorff, 2007). Furthermore, assessing trajectory linearity could also be a balance measure as deviations from the

(a) (b)

Figure 4.2: IMUs' placement (a) and their orientation (side view of right foot) (b).

expected trajectory may be caused by attempts to compensate for poor balance. The detection and count of the number of unbalances could also be useful.

4.3 Signals preprocessing

The analysis of the exercises was performed using only the acceleration, angular velocity and orientation signals. The magnetometer measurements were discarded because it was not possible to control the magnetic interference in the surrounding environment. After obtaining those signals, acceleration and angular velocity were filtered to attenuate noise and smooth the signal.

In order to maintain the synchronisation between sensors of the same IMU, both filters were applied backwards and forward avoiding phase distortion. To choose cut-off frequencies able to smooth the signals without altering its characteristics, power spectral densities (PSDs) of the magnitude of the accelerometer and of the magnitude of the angular velocity were computed. Figures 4.3 and 4.4 present the PSD curves for the magnitude of the acceleration and the magnitude of the angular velocity, respectively.

PSD curves present the power at each frequency which emphasises the frequencies containing the greatest power. Considering that noise is typically non-deterministic, lower in amplitude and has a different frequency range than that of the signal, PSD curves could help set a cut-off frequency that distinguishes between the signal (higher power) and noise (lower power) (Robertson et al., 2004). From the information in Figure 4.3, frequencies between 5 and 15 Hz were experimented for the accelerometer signal, and 10 Hz was the frequency that led to a better outcome. For the gyroscope signal, using information from Figure 4.4, frequencies between 3 and 6 Hz were tested, and 4Hz was the chosen frequency. As the PSD curves were similar for all the exercises, the same filters were used in all of them.

In the implementation, a 4^{th}-order low-pass Butterworth filter with a cut-off frequency of 10 Hz was applied to the acceleration signal (Figure 4.5), and a 4^{th}-order low-pass Butterworth filter

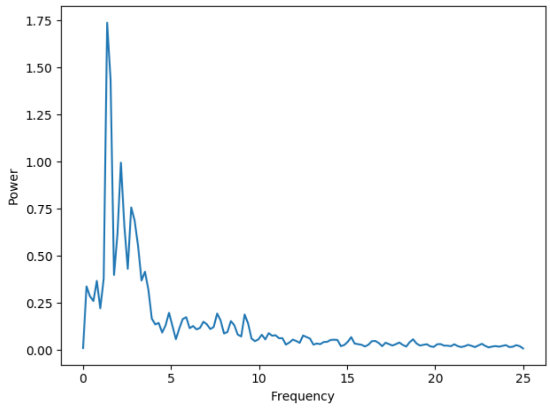


Figure 4.3: Power spectral density of the magnitude of the acceleration in the backwards walking exercise.

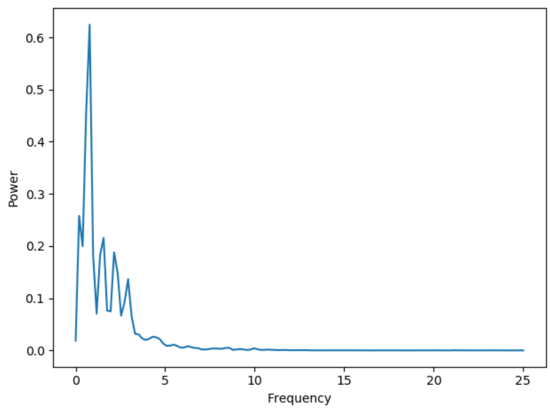


Figure 4.4: Power spectral density of the magnitude of the angular velocity in the backwards walking exercise.

with a cut-off frequency of 4 Hz was applied to the gyroscope signal (Figure 4.6).

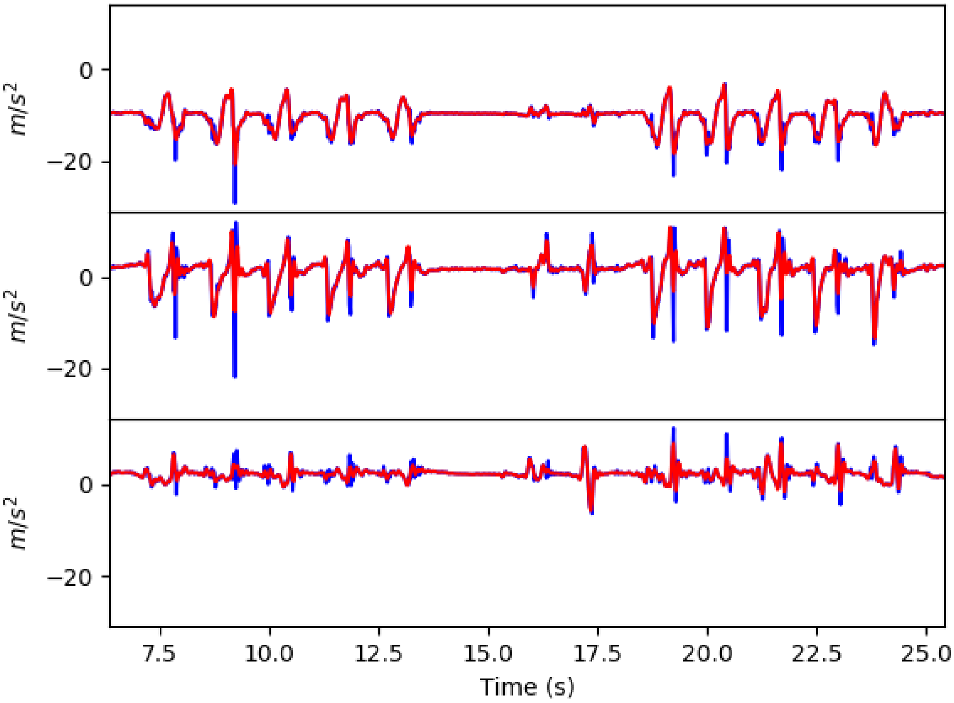


Figure 4.5: Results of the filter application on the acceleration signal in the backwards walking exercise. The original signal is represented in blue, and the filtered signal is presented in red.

4.4 Selected exercises

The exercises selected from the Otago Exercise Programme were:

- backwards walking exercise;
- tandem walking exercise;
- tandem walking backwards exercise;
- heel walking exercise;
- toe walking exercise.

Those exercises were already presented in section 2.5.1.1. A more detailed description with their accelerometer and gyroscope representative signals is presented in the following subsections. The presented signals were all collected with the same subject.

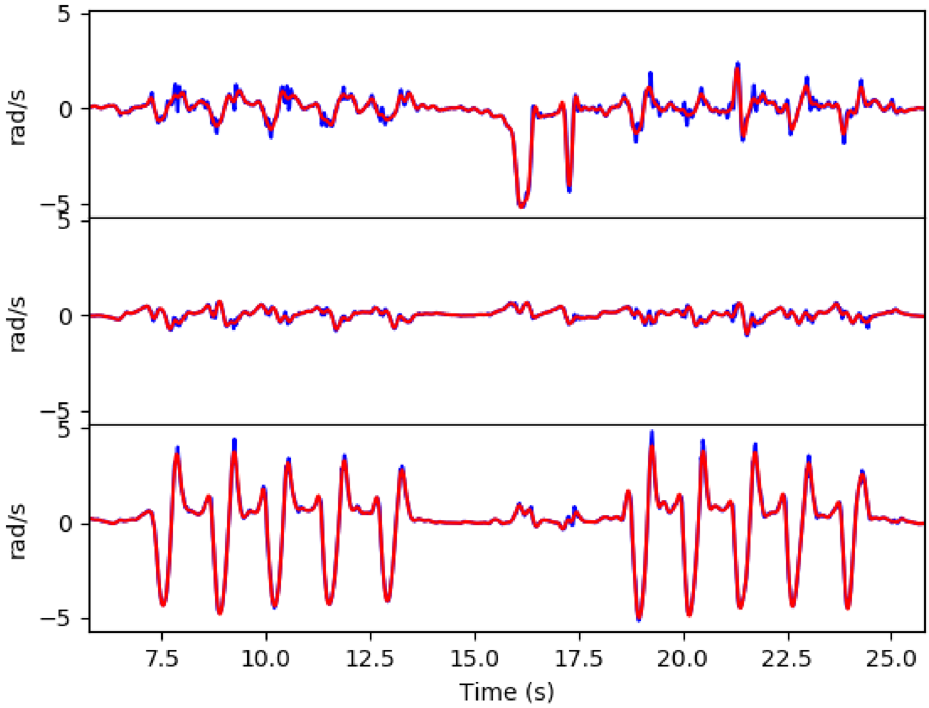


Figure 4.6: Results of the filter application on the angular velocity signal in the backwards walking exercise. The original signal is represented in blue, and the filtered signal is presented in red.

4.4.1 Backwards walking exercise

This exercise consists in taking 10 steps backwards, turning around, and walking 10 more steps backwards. As in normal gait, each stride of this exercise can also be divided into two main phases: swing and stance. However, the sequence of gait events is different which also changes acceleration and angular velocity patterns. Figures 4.7 and 4.8 present representative accelerometer and gyroscope signals, respectively, of this exercise.

In this exercise, each stride starts with an heel-off event. Then the toes leave the floor, and the leg swings backwards. In the acceleration signal, this is represented by an increase (1) of the signal (in absolute value). While the leg swings backwards, there is a deceleration period (2), quickly followed by another acceleration (3) period when the toes and the heel make contact with the floor. Between the heel-strike and the start of another stride, the foot is entirely placed on the floor and the acceleration signal only shows the gravity component and noise (4).

In the angular velocity signal, the stride begins with a small peak (1) related to ankle rotation caused by the heel-off and the toe-off events. The big valley (2) is caused by the leg movement backwards and is followed by another peak (3) due to toe-strike and heel-strike events. When the foot is entirely placed on the floor, the angular velocity is minimal (4).

The described signal variations are more visible in the x- and y-axes of the acceleration signal, and in the z-axis of angular velocity because the exercise is mainly performed in only one direction.

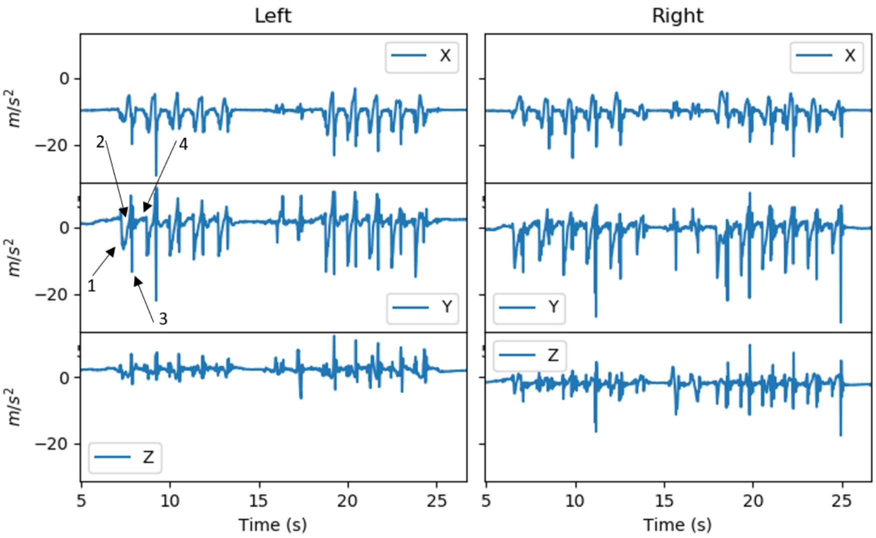


Figure 4.7: Accelerometer signals during the backwards walking exercise.

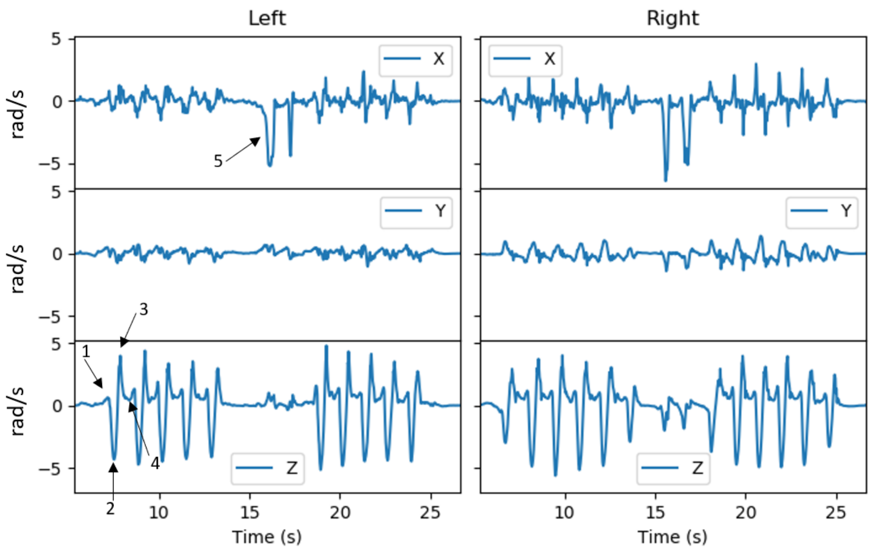


Figure 4.8: Gyroscope signals during the backwards walking exercise.

The turning movement, in the middle of the exercise, is easily identified by big valleys (5) in the x-axis of the angular velocity.

4.4.2 Tandem walking exercise

In this exercise, the subject walks 10 steps, placing each foot directly in front of the other, turns around, and walks 10 more steps in the same manner. This exercise is more similar to forward gait than the backwards walking exercise, but there are also some differences in the acceleration and angular velocity signals. Figures 4.9 and 4.10 present the characteristic accelerometer and gyroscope signals, respectively.

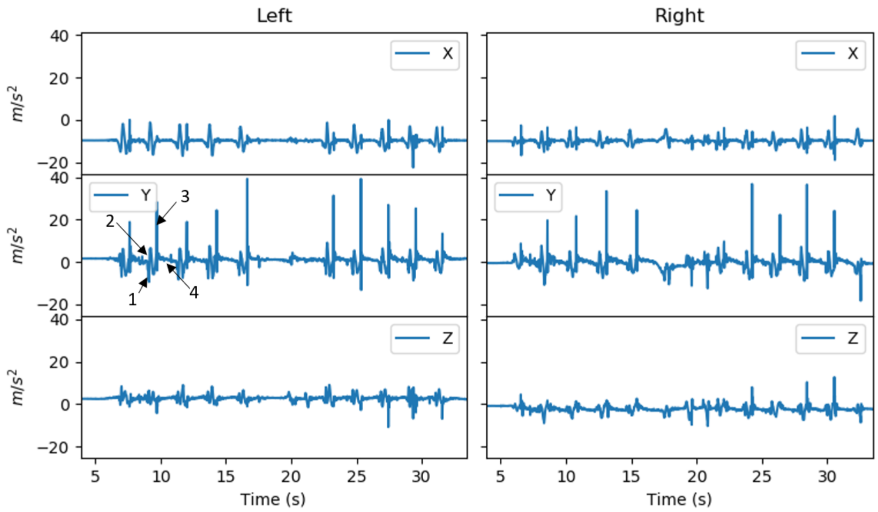


Figure 4.9: Accelerometer signals during the tandem walking exercise.

Each stride starts with the heel-off and toe-off events, causing the first increase in absolute value of acceleration (1). During the swinging movement of the leg, there is a deceleration period (2). The next increase in acceleration's modulus (3) is caused by the heel-strike and toe-strike events. These are followed by a rest period (4). During this period, the foot is entirely placed on the floor, and the accelerometer measures only gravity and some noise.

Regarding the angular velocity signal, the stride starts with a valley (1) related to the ankle rotation, due to heel-off and toe-off events. Afterwards, the signal shows a big peak (2) caused by the leg movement. At the end of the stride, the ankle rotation due to heel-strike and toe-strike causes a small valley (3) in the signal. When the foot is entirely placed on the floor, the angular velocity is minimal (4).

Although this exercise is performed in only one direction, excluding turn movement, all axes of the two IMUs have relevant information regarding the exercise, because, after toe-off, the leg moves to the side and forward in order to go around the opposite leg. The turning movement is also identified by a significant increase of the angular velocity in the x-axis (5).

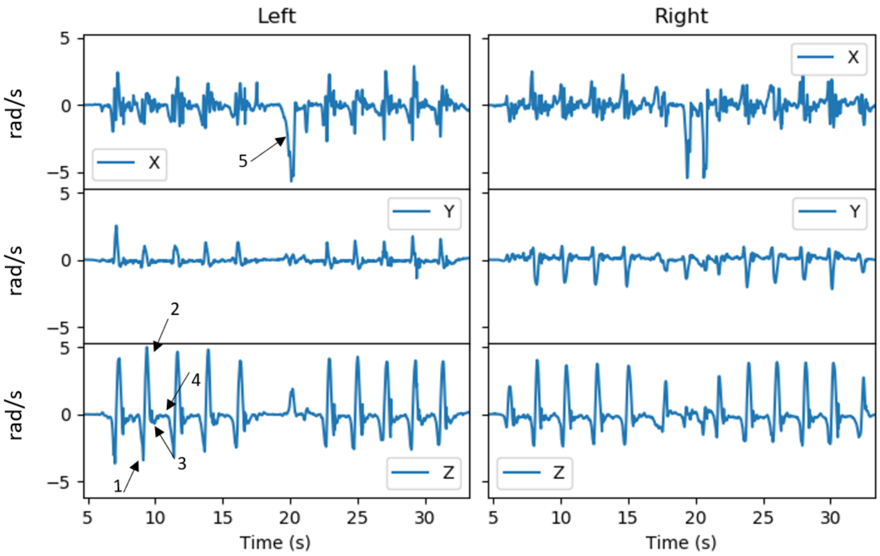


Figure 4.10: Gyroscope signals during the tandem walking exercise.

4.4.3 Tandem walking backwards exercise

This exercise consists in walking 10 steps, placing each foot directly behind the other, turning around, and walking 10 more steps in the same manner. The characteristic acceleration and angular velocity signals are presented in Figures 4.11 and 4.12, respectively.

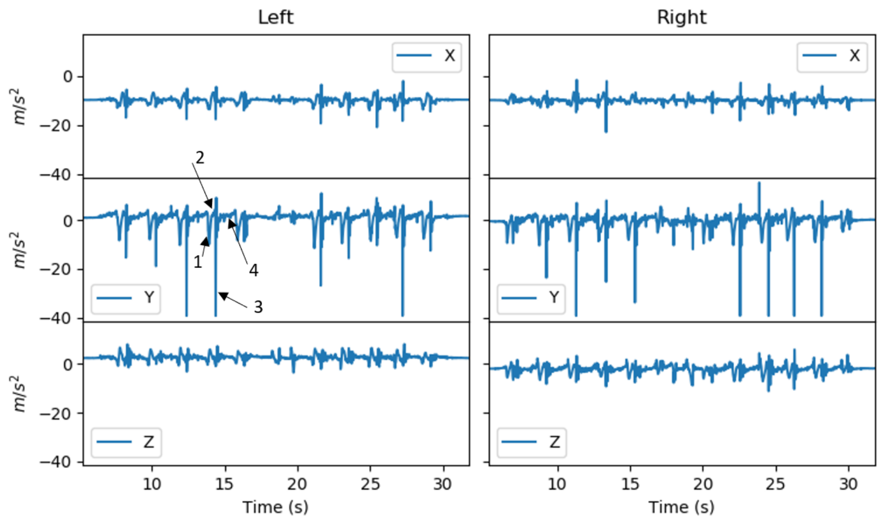


Figure 4.11: Accelerometer signals during the tandem walking backwards exercise.

Each stride starts with the heel-off and toe-off events, increasing the absolute value of the acceleration signal (1). Then, the leg moves to the side and in front. There is a small deceleration (2) during the movement of the leg, followed by another acceleration (3) period when the foot

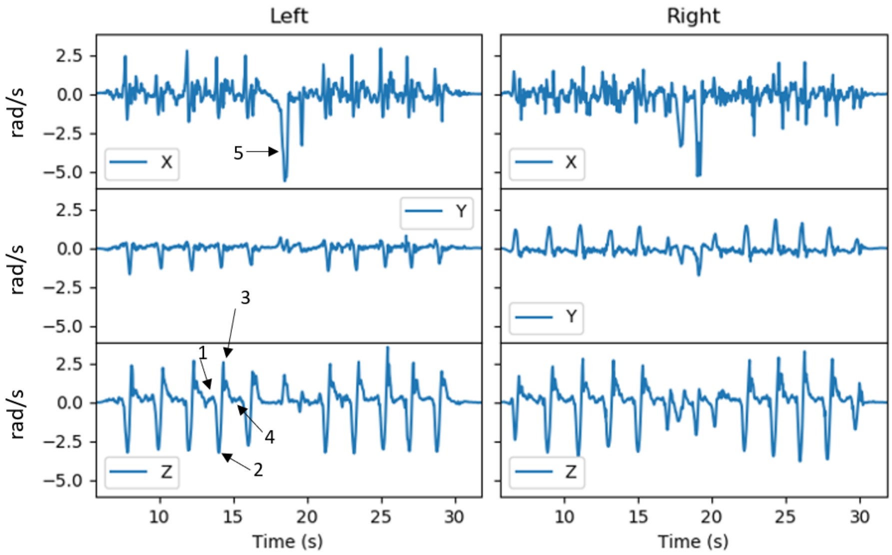


Figure 4.12: Gyroscope signals during the tandem walking backwards exercise.

touches the floor. The initial contact is made with the toes, followed by the heel. Afterwards, there is a rest period (4) until another heel-off event starts another stride.

The angular velocity signal is similar to the one of tandem walking only inverted. The first peak (1) is the result of the ankle rotation due to the heel-off and toe-off events, followed by a big valley (2) representing the swing movement of the leg, and another smaller peak (3) that results from the heel-strike and toe-strike events. After, there is a rest period and the angular velocity is close to zero (4).

Similarly to the tandem walking exercise, the present exercise also has relevant information in all of the IMUs' axes because of the leg movement in front and to the side during the swing phase, and the turning movement is identified by a significant increase of the angular velocity in the x-axis (5).

4.4.4 Heel walking exercise

This exercise consists in walking 10 steps on heels (without lowering the toes to ground), turning around, and walking 10 more steps on heels. In this exercise, the toe-off and toe-strike events do not exist. Therefore, acceleration and angular velocity characteristic patterns will change accordingly. Figures 4.13 and 4.14 present the acceleration and angular velocity signals, respectively, of a heel walking exercise.

Starting with the toes off the floor, each stride starts with the heel-off event, followed by the leg swing movement, the heel-strike and a brief resting period. The absolute value of the acceleration increases (1) when the heel is lifted off the floor, decreases (2) during the leg swing movement, and increases (3) again when the heel is placed on the floor. Then, there is a brief period when the foot does not move and the accelerometer measures only the earth's gravity and noise (4).

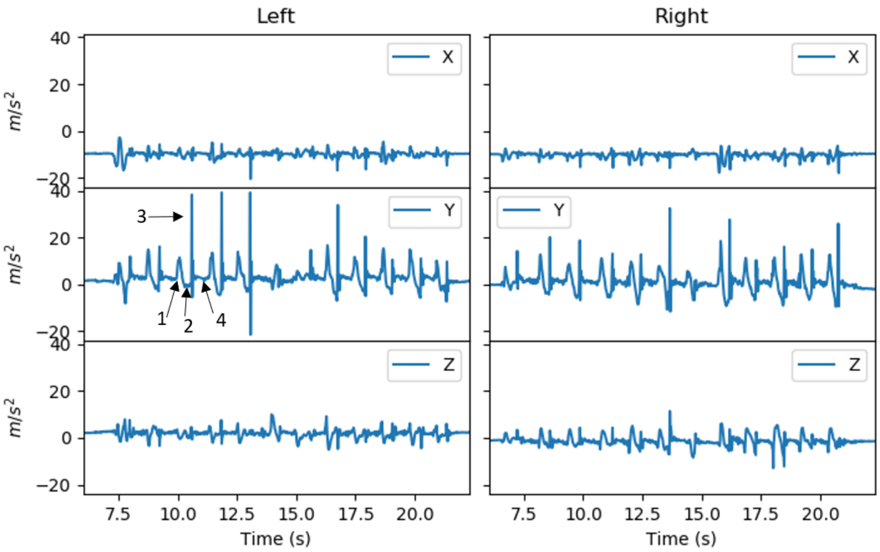


Figure 4.13: Accelerometer signals during the heel walking exercise.

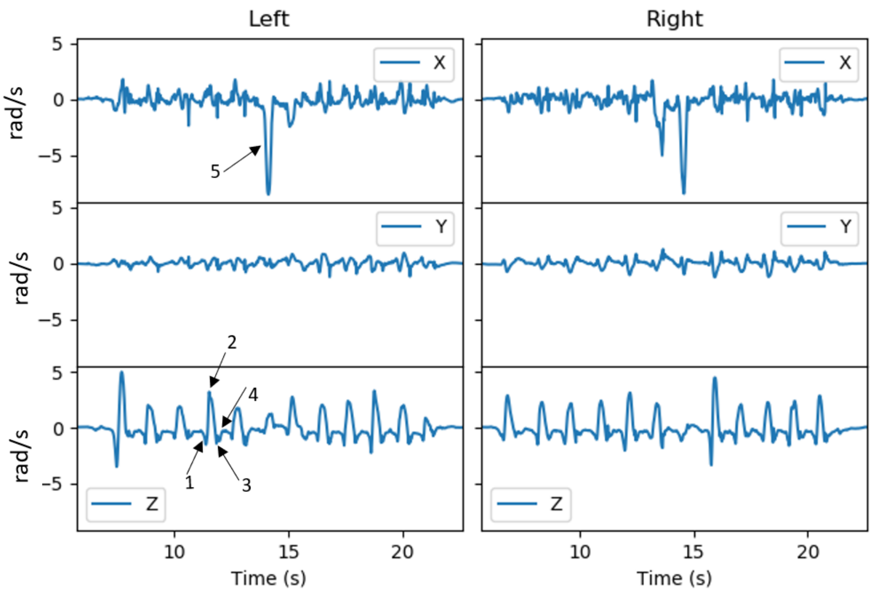


Figure 4.14: Gyroscope signals during the heel walking exercise.

The angular velocity pattern is similar to the previous exercises with one big peak surrounded by two smaller valleys in the z-axis. The peak (2) is also caused by the swing motion of the leg. Although this exercise does not have toe-off and toe-strike events, the ankle joint still has a rotation movement that is identified in the collected signals when the foot is lifted (1) or placed (2) on the floor. The valleys in the angular velocity signal are the result of those rotations. After, there is a rest period and the angular velocity is close to zero (4). In the x-axis of the angular velocity, the bigger valleys (5) are related to the turn movement.

4.4.5 Toe walking exercise

This exercise consists in walking 10 steps without lowering the heels to the floor, turning around and walking 10 more steps in the same manner. Similarly to the heel walking exercise, not all usual gait events occur in this exercise. Heel-off and heel-strike should not happen while toe-walking. The acceleration and angular velocity signals of this exercise are presented in Figures 4.15 and 4.16, respectively.

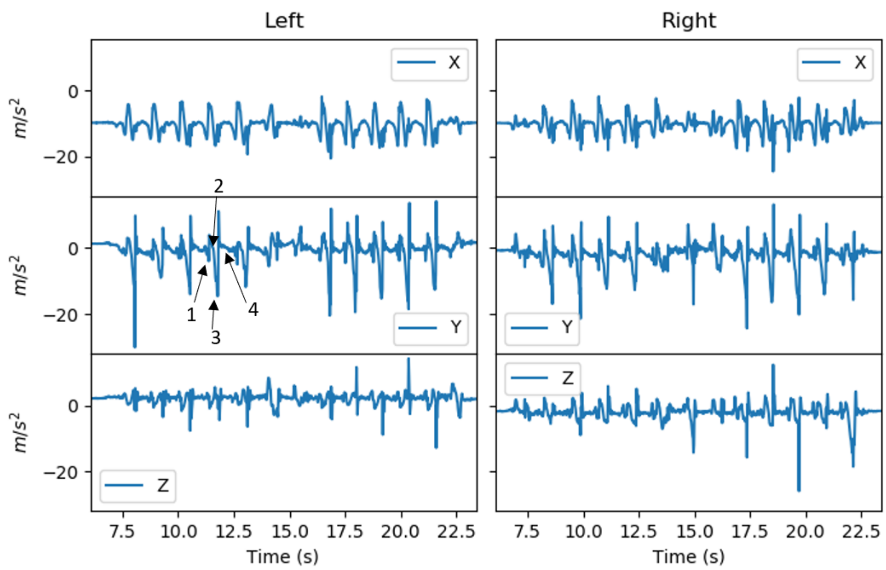


Figure 4.15: Accelerometer signals during the toe walking exercise.

Starting with the heels lifted, each stride starts with the toe-off event, followed by a swing movement of the leg, toe-strike and a brief resting period until the start of a new stride. The acceleration increases (1) at the start of the stride, when the toes are lifted off the ground, decreases (2) during the swing movement and increases (3) again at the toe-strike event. Then, there is a period when the accelerometer measures only the earth's gravity and some noise (4) because the foot is not moving.

The angular velocity pattern is also similar to the previous exercises. The stride pattern in the z-axis includes a big peak surrounded by two smaller valleys. The peak (2) corresponds to the swing motion of the leg, and the valleys identify the moments when the foot is lifted (1) and placed

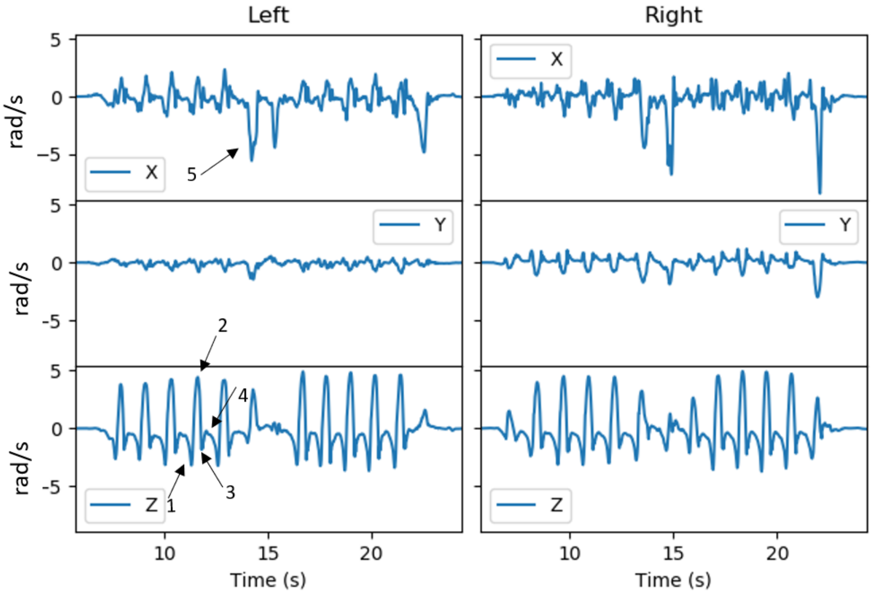


Figure 4.16: Gyroscope signals during the toe walking exercise.

on the floor (3). There is also a period when the angular velocity is close to zero (4) because the foot is not moving. The turning movement is easily identified by the big valleys in the x-axis (5).

4.5 Stride Segmentation

Examples of the selected exercises in the literature are scarce. The relation between the combination of acceleration and angular velocity signals with gait events is not well studied, and possible variations due to gait impairments are also not described. Therefore, the approach to stride detection and segmentation was developed to be robust and to segment only between stationary, similar to the foot-flat phase, and non-stationary phases. This segmentation was chosen because both phases were easily identifiable, without any previous knowledge of the relation between the acceleration and angular velocity signals and the events they represent, and, also, because this division would be useful in the stride length estimation as it will be explained in section 4.7.

Signal patterns are different for each exercise, but the similarities between them enable the use of the same stride segmentation method for all.

In all exercises, there is a well-defined pattern in the z-axis of the angular velocity formed by a big peak surrounded by two smaller valleys in forward exercises, and a big valley surrounded by two smaller peaks in backwards exercises. Each stride was detected by identifying the big peaks or valleys representing mid-swing moments. Those moments were identified by detecting peaks or valleys (depending on the exercise) with a minimum height of $1 rad/s$ and a minimum distance from other peaks of 37 samples $(0,74s)$. These values were chosen empirically. Figure 4.17 presents the results of the stride detection.

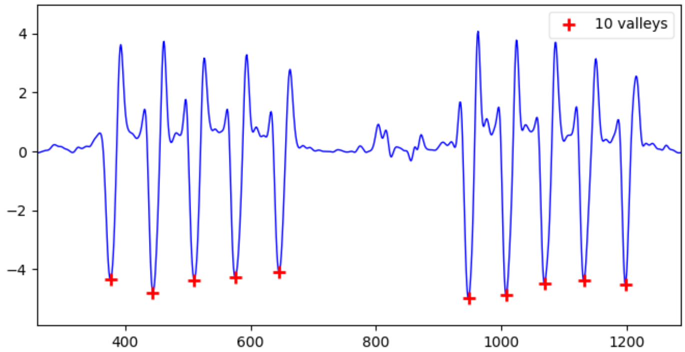


Figure 4.17: Stride detection results in the backwards walking exercise.

After stride detection, the limits for stationary and non-stationary phases were identified using the moving variance of the magnitude of the acceleration signal. Stationary phases are characterised by little variations in the acceleration signal, and the intensity of those variations can be assessed using the moving variance (Wang et al., 2013). The magnitude of the acceleration signal, a_{mag} is an invariant signal which means it is independent of the sensor orientation, and it was computed with equation 4.1 where a_x, a_y and a_z are the acceleration values of the x, y and z-axes, respectively.

$$a_{mag} = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{4.1}$$

Moving variance, D, was calculated using equations 4.2 and 4.3 where i and j are samples indexes, M is the size of the sliding window, and $E(i)$ is the mean of the sliding window centred in sample i.

$$E(i) = \frac{1}{M} \sum_{j=-\frac{M}{2}}^{\frac{M}{2}} a_{mag}(j+i) \tag{4.2}$$

$$D(i) = \frac{1}{M} \sum_{j=-\frac{M}{2}}^{\frac{M}{2}} [a_{mag}(j+i) - E(i)]^2 \tag{4.3}$$

The effect of the sliding window size is presented in Figure 4.18. Small window sizes are too sensible to the acceleration variations while big sizes lead to loss of information. In this particular case, the moving variance was needed to segment strides into stationary and non-stationary phases. Therefore, the ideal size would lead to small variance values in stationary phases and high values otherwise. That was obtained when using a window size approximately the same size as the non-stationary phases. However, that optimal size changed according to the speed, exercise, and subject. In this work, the size of the sliding window was chosen empirically and set as 25 samples. However, in future developments, the use of an adaptive window size may improve stride segmentation results.

In order to set limits for the gait phases, one could be tempted to use a fixed threshold because the differences between moving variance values in each phase were easily observed in Figure 4.18.

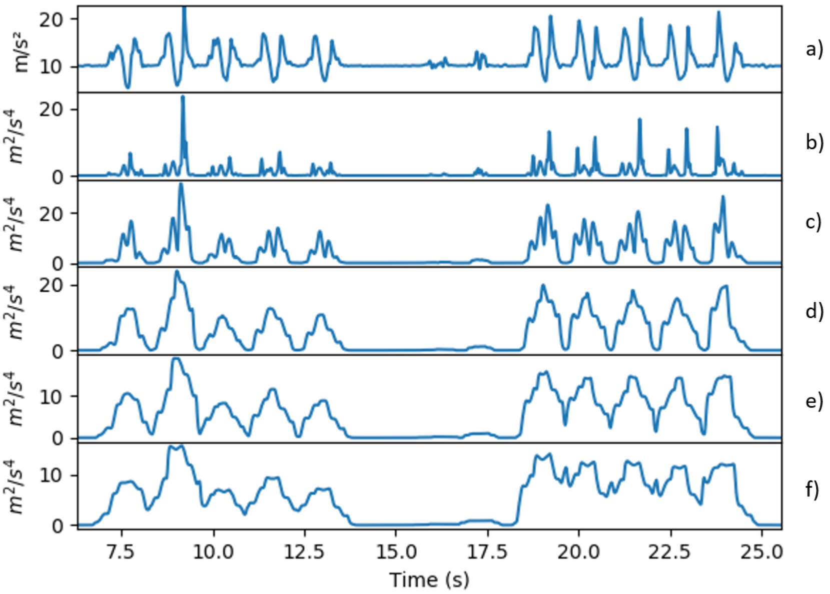


Figure 4.18: Effect of the sliding window size in moving variance results in the backwards walking exercise. (a) shows the magnitude of the acceleration signal. (b), (c), (d), (e), and (f) show the moving variance results for windows of size 5, 15, 25, 35, and 45, respectively.

However, there was not an optimal value for a fixed threshold because that value was dependent, for example, of the subject and walking speed. Therefore, an adaptive threshold approach was used.

As it is possible to see in Figure 4.19, previously detected peaks in the angular velocity signal were in the non-stationary phase. For each of the previously detected strides, the start of non-stationary (SN) phase was set as the last sample, between the current stride peak and the previous one, to have a moving variance value lower than 10% of the moving variance value at the stride peak. The end of the non-stationary phase (EN) was set as the first sample, between the current stride peak and the next one, whose moving variance value was higher than 10% of the moving variance value at the detected peak.

Afterwards, two errors could be detected. One was the possibility of not finding a sample lower or higher than the threshold to set as SN or EN, respectively. In that case, only for that stride and for the limit that was not found, the threshold was lifted in increments of 5% until a suitable sample was found. The other possible error was when the EN of the previous stride is set to a sample after the SN of the current stride. In that case, EN of the previous sample was set as the sample with the lower moving variance value between the two peaks and the SN of the current sample was set as the next sample.

This entire process was repeated for both limbs. Stride segmentation results are presented in Figure 4.20.

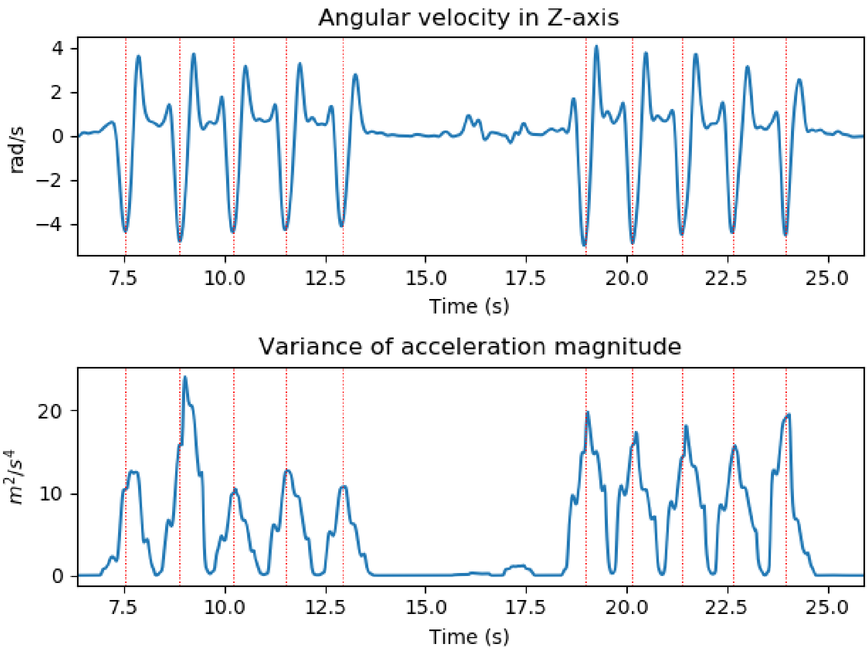


Figure 4.19: Relation between the valleys in the angular velocity and the moving variance in the backwards walking exercise.

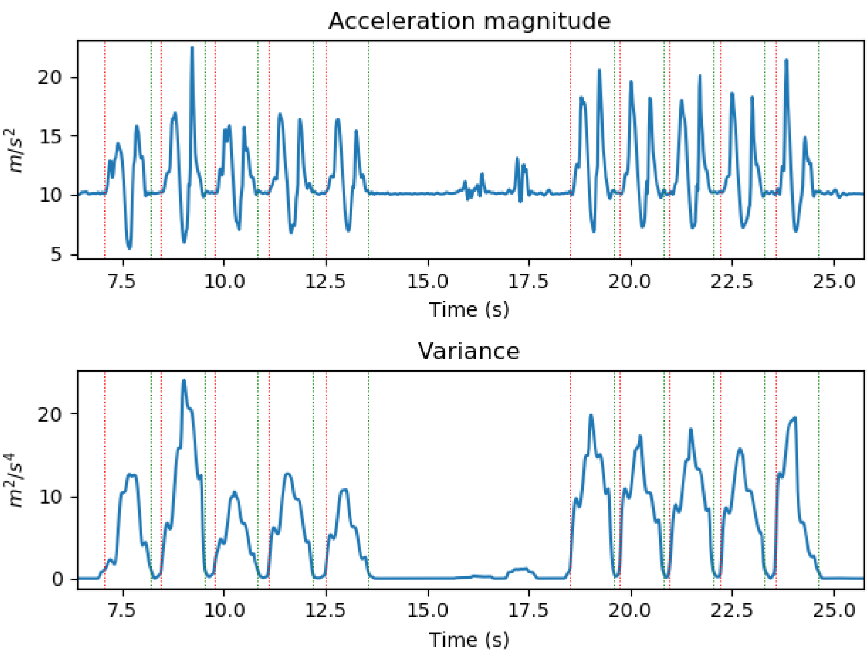


Figure 4.20: Results of stride segmentation on the magnitude of the acceleration signal (a) and on the variance of the acceleration signal (b) for the backwards walking exercise. Red lines represent SN and green lines represent EN.

4.6 Turning Detection

All the selected exercises contain a turning movement, and the subject could perform that movement in the most comfortable manner. For example, the number of steps taken while turning is not defined. Therefore, at least for now, the turning movement does not provide useful information to the analysis of the exercise, and its detection was performed to discard any strides detected during that movement, and to distinguish between strides taken before and after turning.

The approach used to detect the turns was based on the work of El-Gohary et al. (2014). The angular velocity around the vertical axis is the ideal signal to detect turns. In order to obtain that signal in the world frame, ω_z^w, equation 4.4 was used to transform the angular velocity measured in the sensor frame, ω^s, into the world frame, ω^w. q represents the orientation signal.

$$\omega^w = q \odot \omega^s \odot q^{-1} \tag{4.4}$$

Afterwards, peaks with an absolute value higher than $15^o/s$ in the ω_z^w signal were identified as candidate turns, i. The start, ts_i, and the end, te_i, of each of those candidates were set to the sample where ω_z^w dropped below $5^o/s$.

Considering that it is difficult to make a turn in less than $0.5s$ and in more than $10s$ (El-Gohary et al., 2014), candidate turns whose duration were not between 0.5 and $10s$ were discarded. Finally, only turns whose turn angle was higher than 45^o were considered. The turn angle for each candidate turn i, θ_z^i, was obtained with equation 4.5.

$$\theta_z^i = \int_{ts_i}^{te_i} \omega_z^i(t)dt \tag{4.5}$$

Then, each turn was characterised by a start time and an end time forming a time segment. This process was repeated for both limbs because the turning movement does not start at the same time in both. In order to obtain only a start and an end time for the whole movement, it was necessary to combine the results from both limbs. So, the results of one side were merged with overlapping time segments of the other side.

Only one turn should be detected during each exercise, but more could be identified if the subject turned around right after ending the exercise. In order to avoid those errors, the turn could not be detected in the first or the last 2 seconds of the exercise and had to have more than one detected stride before and after.

Finally, after obtaining the start and the end of the turn, strides detected between those instants were discarded. If the subject does not stop after walking the first 10 strides and before starting to turn and/or does not stop after completing the turn and before starting to walk the 10 last strides, it is possible to start or end an exercise stride while the other limb ends or starts, respectively, the turn. To avoid discard and lose data about strides that still belong to the exercise, if the turn started or ended in the middle of a stride, that stride is only discarded when more than 50% of its non-stationary phase overlapped with the turn.

4.7 Stride length and Trajectory Estimation

The used approach to estimate stride length was based on the double integration of acceleration measurements. Although this type of approach has some challenging problems, their ability to estimate displacements in three-dimensions, deduce trajectories, and consequently provide information about balance, made it the most convenient for this work.

Stride length is a measure defined in the world frame. So, the accelerometer measurements in the sensor frame, a^s, were transformed into the world frame, a^w, using equation 4.6 where q is the quaternion describing the orientation of the IMU. The results are presented in Figure 4.21.

$$a^w = q \odot a^s \odot q^{-1} \tag{4.6}$$

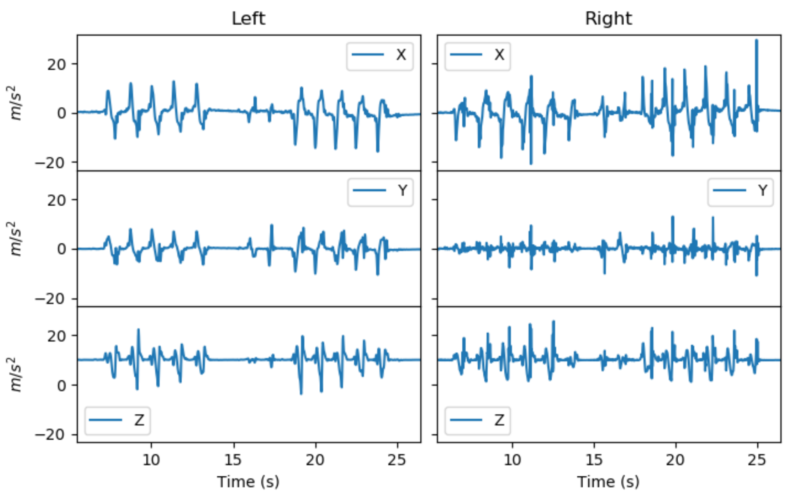


Figure 4.21: Acceleration signal of a backwards walking exercise in the world frame.

Accelerometers measure the external specific force acting on the sensor. The specific force consists of both the earth's gravity and the device's acceleration (Kok et al., 2017). Before integrating the accelerometer measurements, gravity's component had to be removed. Considering that earth's gravity, g, is a vertical force pointing to the centre of the earth and that its value is $9.8m/s^2$, the device's acceleration, a^w_{IMU}, could be computed using equation 4.7 (Rebula et al., 2013; Bishop and Li, 2010).

$$a^w_{IMU} = a^w - \begin{bmatrix} 0 \\ 0 \\ 9.8 \end{bmatrix} \tag{4.7}$$

Afterwards, stride length was calculated stride by stride applying a ZUPT technique similarly to Wang et al. (2013). Velocities in x- and y-directions (of the world frame) were computed using equations 4.8 and 4.9, respectively. The velocity for each stride and it was assumed that in the stationary phase velocity was zero. ax^w_{IMU} and ay^w_{IMU} are the x and y axes, respectively, of the acceleration signal in the world frame without the gravity component.

$$v_x(i) = \int ax^w_{IMU}(t)dt \tag{4.8}$$

$$v_y(i) = \int ay^w_{IMU}(t)dt \tag{4.9}$$

Before doing the second integration and obtaining stride length, integration drift in the velocity estimation needed to be corrected. First, the velocity difference between the start, v_{SN}, and the end, v_{EN}, of the non-stationary periods, Δv, was computed as shown in equation 4.10.

$$\Delta v = v_{SN} - v_{EN} \tag{4.10}$$

After, the drift rate was obtained by dividing Δv by the number of samples in that period, equation 4.11.

$$drift\ rate = \frac{\Delta v}{EN - SN} \tag{4.11}$$

Then, drift value at each sample was obtained by multiplying the drift rate by the corresponding data index, j, 4.12.

$$drift\ value(j) = drift\ rate \times j \tag{4.12}$$

The corrected velocity, v_{corr}, was obtained subtracting the drift value at each point from the previously computed velocity, equation 4.13 (Zhi, 2016).

$$v_{corr}(j) = v(j) - drift\ value(j) \tag{4.13}$$

Afterwards, stride length in each of the directions, l_x and l_y, was computed according to equations 4.14 and 4.15. vx_{corr} and vy_{corr} are the corrected velocities in the x- and the y-directions, respectively.

$$l_x(i) = \int_{SN(i)}^{EN(i)} vx_{corr}(t)dt \tag{4.14}$$

$$l_y(i) = \int_{SN(i)}^{EN(i)} vy_{corr}(t)dt \tag{4.15}$$

After obtaining the stride length in each of the directions, the trajectory could be reconstructed. Without considering the initial distance between feet, it was assumed that both started in position (0,0). Consecutive positions were obtained by summing the displacement in the x-direction to the previous coordinate in the x-axis, and the same for the y-direction. The trajectory was reconstructed separately after and before turning, and the results are presented in Figure 4.22.

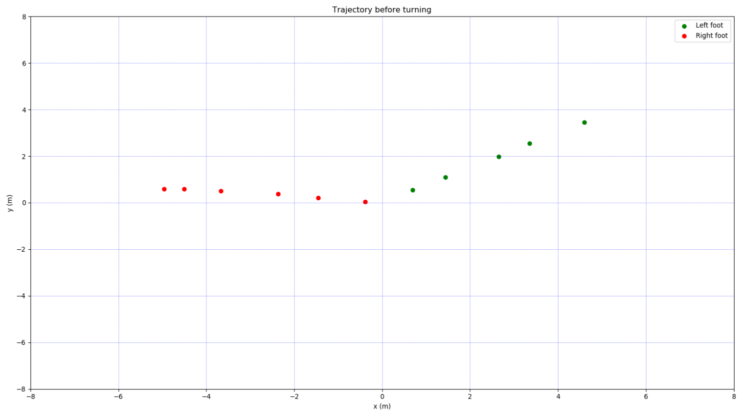


Figure 4.22: Trajectory estimation results before turning. Red dots mark successive positions of right foot and green dots mark successive positions of left foot.

From the inspection of Figure 4.22, it is possible to conclude that trajectory reconstruction was not successful. Since it was considered that both feet started at the same position, all the marks should be in a straight line in the same direction even with small deviations due to unbalances and step width variations. Besides, although some drift in orientation is expected (Bachmann et al., 2012), the trajectory should be mostly in the x-direction or in the y-direction.

These errors appear to be caused by difficulties in estimating orientation. The orientation estimation algorithm was already developed. It is part of the application that collects data from the sensor, and only relies on the data of the accelerometer and the gyroscope. The accelerometer provides information about the vertical direction by measuring the direction of the gravity (Kok et al., 2017). However, without magnetometer data, there is no reference about North direction, and the x and y-directions are assigned to two random perpendicular directions. Therefore, the orientation information provided by the IMUs were quaternions that represented the rotation between the sensor frame and a world frame consisting of a vertical axis and two perpendicular horizontal axes.

The main issue is that, contrary to the initial assumption, the quaternions obtained from the IMUs do not represent the rotation between each of the devices' frames and the same world frame. This is suggested by the trajectory results showing each foot and attached IMU going in different directions and also by Figure 4.21. Due to the periodic characteristics of gait, the acceleration signals should vary similarly despite the phase delay. However, that does not happen in the x and y-axes of the IMUs. In the left x-axis, each stride begins with a positive peak, and, in the right x-axis, each stride begins with a negative peak. Also, the left y-axis shows an easily identifiable pattern that is not present in the right y-axis. Both z-axes show a similar pattern which suggests that the vertical direction was the same for both world frames, and that the difference between them was a rotation around the vertical axis.

Unfortunately, the difference between the world frames was not constant in all of the tests performed, it was not identified a behaviour (i.e. standstill at the beginning of the exercise) to avoid that difference, and no method to align the frames after recording the signals was successful. Therefore, the trajectory was not used to evaluate the exercise performance and balance.

For the reasons appointed before, the x- and y-axes did not refer to the forward and side (or vice versa) directions of gait. So, stride length, *SL*, was defined as the norm of the vector containing the displacements in the x- and y-directions, equation 4.16.

$$SL(i) = \left\| \begin{array}{c} l_x(i) \\ l_y(i) \end{array} \right\| = \sqrt{l_x(i)^2 + l_y(i)^2} \tag{4.16}$$

4.8 Shank-to-vertical angle

As described in section 4.1.2, placing the sensor in the ankle or shank has several advantages over placing the sensor in the foot. However, without the use of any other sensors, such as in Chen et al. (2011) where an additional IMU was placed in the foot, it was not possible to compute the ankle joint angle, Figure 4.23, because the foot and the shank are segments that move independently (Owen, 2010). Nevertheless, estimating the shank-to-vertical angle (SVA) can provide information regarding shank kinematics.

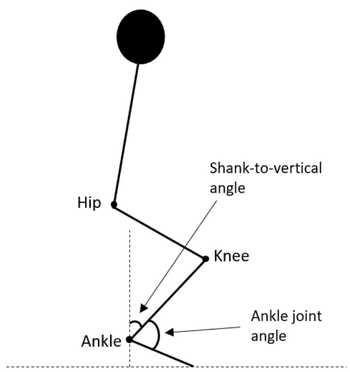


Figure 4.23: Ankle joint angle and shank-to-vertical angle (SVA).

The SVA can be described as the angle between the shank and the vertical, measured in the sagittal plane, Figure 4.23 (Eddison et al., 2017). This parameter is commonly computed to tune and evaluate the designs of ankle-foot orthoses (AFOs) (Jagadamma et al., 2009). These devices are prescribed to patients who exhibit abnormal lower-limbs kinematics, particularly in the shank segment, to normalise joint kinetics and kinematics while walking (Eddison et al., 2017). Normalization of shank kinematics, specially, during the mid-stance phase, contributes to the optimisation of thigh and trunk kinematics, knee and hip kinetics and stability during stance phase (Owen, 2010).

In order to calculate the SVA during the exercise, an initial reference vector was defined as the mean acceleration vector, a^s_{ref} in $1s$ before the exercise started. Then, that vector was transformed into the world frame, a^w_{ref}, according to equation 4.17. a^w_{ref} represented the vertical direction.

$$a^w_{ref} = q \odot a^s_{ref} \odot q^{-1} \tag{4.17}$$

After the exercise started, for every sample i, the initial reference vector, a^s_{ref}, was transformed into the world frame, $a^w_i(i)$, using the orientation data of that sample. The SVA was the angle between a^w_{ref} and $a^w_i(i)$ and it was computed using equation 4.18.

$$SVA(i) = cos^{-1}\left(\frac{a^w_{ref} \cdot a^w_i(i)}{\parallel a^w_{ref} \parallel \times \parallel a^w_i(i) \parallel}\right) \tag{4.18}$$

The results of angle estimation for the backwards walking, tandem walking, tandem walking backwards, heel walking and toe walking exercises are presented in Figures 4.24a, 4.24b, 4.24c, 4.24d and 4.24e, respectively. As it is observable in those figures, at the beginning of each stride the angle increased. It decreased during swing phase when the swinging leg was parallel to the support leg, increased again and it was minimal in stance phase. Even though this sequence of events is present in all exercises, the timing in which they happen is different.

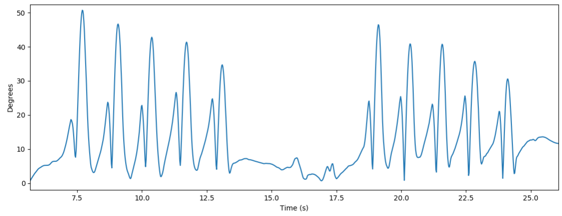
4.9 Gait symmetry

For assessing gait symmetry, several parameters were calculated for each limb and for each stride. Gait parameters should be computed in a steady state gait with constant gait speed to avoid irregularities in the gait pattern that may be associated with the initiation and termination of it (Lindemann et al., 2008). Therefore, other works have excluded several initial and final strides (Kobsar et al., 2014; Wang et al., 2013).

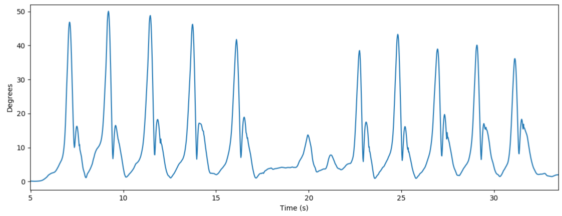
In this work, only the first and last stride before turning and the first and last stride after turning of each limb were excluded because the analysed exercises consist in only two segments of 10 strides separated by a turn. This may not be sufficient to collect data from a steady state gait, but averaging data from more than one repetition of the exercise could minimise the irregularities due to the initiation and termination of the exercise.

The parameters computed for each stride were minimum, maximum, mean and variance of the magnitude of acceleration; minimum, maximum, mean and variance of the magnitude of angular velocity; minimum, maximum, mean and variance of the SVA; duration and percentage of the non-stationary phase in the GC; and duration of the stationary phase. While parameters regarding gait phases duration and variability are more common in literature, parameters based on the IMU data were also computed because they depend less on the accuracy of the stride segmentation and could provide additional information.

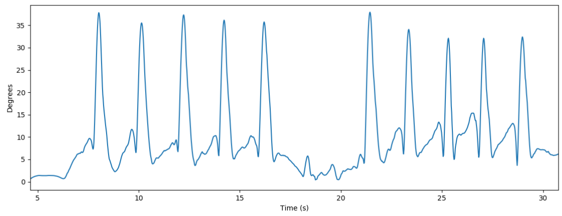
The computed parameters were compared using a statistical test as in Exell et al. (2012) where paired *t*-tests were used to compare gait features from both limbs. However, in this work, for each limb and gait parameter, the number of values was small, and normality cannot be assumed.



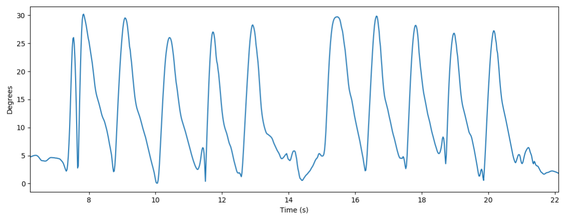
(a)



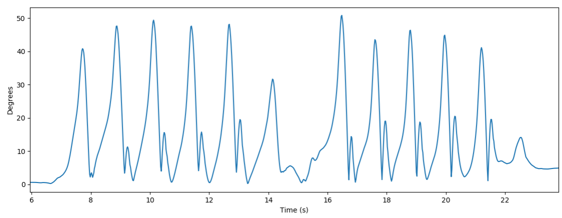
(b)



(c)



(d)



(e)

Figure 4.24: SVA estimation results in backwards walking (a), tandem walking (b), tandem walking backwards (c), heel walking (d) and toe walking exercises (e).

Therefore, it was used the Wilcoxon Signed Rank test which is the non-parametric equivalent of paired t-tests (Pallant, 2010).

4.10 Experimental Protocol

In order to validate the used methodology, data were collected from a group of 14 older adults (Group 1) and a group of 14 younger adults (Group 2). Table 4.1 presents each group's characteristics. Group 1 members were healthy older adults that did not need walking aids and were recruited by the "Colaborar", a network of contacts Fraunhofer AICOS has developed with elderly people who collaborate in research projects. Group 2 members were recruited among Fraunhofer AICOS researchers. Every participant provided signed informed consent to data collection and analysis and video-recording.

Participants were asked if they had any walking difficulties, and if they had had any surgery, lesion or other physical impairment that could affect gait, such as twisted ankles and knee surgeries. The answers to these questions are also summarised in table 4.1. These answers were not used to exclude people with walking impairments or to obtain more homogeneous groups of participants, but to help results interpretation.

Table 4.1: Groups' characteristics (mean ± standard deviation)

	Group 1	Group 2
Number of participants	14	14
Age (years)	73,2 ± 4,4	23,5 ± 1,6
Height (m)	1,61 ± 0,10	1,73 ± 0,07
Weight (kg)	70,8 ± 11,6	72,7 ± 12,9
Number of participants experiencing walking difficulties	4	0
Number of participants reporting right limb impairments	3	0
Number of participants reporting left limb impairments	0	1
Number of participants reporting impairments in both limbs	2	1

Before starting the data acquisition, the Pandlets were placed as described in section 4.1.2, and the exercises were explained to the participants. They were explained once at the beginning of the session and again before the execution of each exercise. Participants were asked to start behind a line marked on the floor, and to wait for a verbal cue to start the exercise. Participants performed each exercise twice at a self-selected speed in the following order: backwards walking, tandem walking, tandem walking backwards, heel walking and toe walking. If necessary, they could rehearse the exercise and rest between trials. During exercise execution, group 1 members were accompanied by, at least, one person that could offer help to avoid falls and injuries, if needed.

The exercises were performed on a marked path while being video-recorded. The path was 7 metres long, and it was marked with transversal lines spaced 50 centimetres apart. In order to avoid any misunderstandings regarding expected stride length, participants were told to ignore those lines. The experimental setup is presented in figure 4.25. The instant the sensors started recording data was also recorded on video to synchronise data between the Pandlets and the camera.

Figure 4.25: Experimental setup. The participants performed the exercises on the marked path while being video-recorded.

Altogether, data from 56 tests were collected for each exercise. Some had to be excluded due to IMUs malfunctions (i.e. IMU disconnected from the computer) or camera malfunctions (i.e. blurred image): in the backwards walking exercise, 2 tests were excluded; in the tandem walking exercise, 3 tests were excluded; in the tandem walking backwards test, 3 tests were excluded; in the heel walking exercise, 3 tests were excluded; in the toe walking exercise, 2 tests were excluded.

4.11 Annotation Process

Participants were video-recorded while performing the exercises. Those videos were, then, manually annotated using Kinovea, a video analysis software designed for coaches, athletes and medical professionals (Kinovea, 2018). The annotations from the videos were considered the ground truth. In each video, the times corresponding to the start and the end of each non-stationary phase, stride and turn were annotated. The distance walked in the longitudinal direction in each stride was also estimated from the video. Despite practice, this procedure was notably time-consuming, given the sample size, number of exercises and the number parameters registered and compared. Furthermore, video examination was fundamental to interpret some of the obtained results, which implied a second analysis of it.

The start of the non-stationary phase (SN) is also the start of the stride and the end of the previous one. The first frame where a movement of the foot (i.e. heel rising) was observable after a rest phase was considered the SN. The end of the non-stationary phase (EN) was considered the first frame where the position of any part of the foot did not change when compared to the previous frame.

The turn included all the events from the frame where the foot started moving (turn start) to the frame where both feet were at rest (turn end). If the participant did not stop after walking the first steps and before starting turning, it was possible that one limb started to turn before the opposite limb ended a stride that still belonged to the exercise. In those cases, turn start was defined as the frame after the stride finished. It was also possible that the participant did not stop after turning and before starting doing the rest of the exercise, and a stride belonging to the exercise could be initiated before the opposite limb completed the turning movement. In those cases, the turn end was defined as the frame before the stride started.

Since only one camera was used, there were some unavoidable inaccuracies in the video annotations. For example, the start of a stride in tandem walking can be hidden by the other foot placed directly in front. Therefore, small errors in the determination of temporal events are expected. Also, there were some cases when it was not possible to correctly determine the stride length and the temporal events because the participant ended the exercise outside of the camera's field of view (i.e. walked more than 7 metres). In those situations, it was still possible to count the number of steps walked, and the corresponding SN and EN were estimated but not compared to results of the developed method because they would be a significant source of error.

4.12 Statistical analysis

The gait parameters evaluated in this work were compared between the two groups. The gait parameters compared were minimum, maximum, mean and variance of the magnitude of the acceleration signal; minimum, maximum, mean and variance of the magnitude of the angular velocity signal; minimum, maximum, mean and variance of SVA; duration and coefficient of variation (CoV) of the non-stationary phase, duration and CoV of stride and the percentage of the GC spent in the non-stationary phase. The CoV is a measure of variability defined as $standard\ deviation/mean \times 100$ (Kobsar et al., 2014). For each participant, gait parameters were averaged between limbs and exercises repetitions, assuming that the velocity between repetitions did not vary significantly.

Gait parameters such as the percentage of time spent in each of the phases, variability of stride duration and acceleration parameters vary according to the velocity (Hamill et al., 2015). Therefore, each gait parameter was compared using a one-way analysis of covariance (ANCOVA) with velocity as the covariate. ANCOVA is a statistical test used when one wants to statistically control for the possible effects of an additional confounding variable (covariate). This statistical test assumes that there is a linear relationship between the covariate and the dependent variables (the gait parameters) in all groups (Pallant, 2010).

Group 2 was formed by younger people who were expected to have a better balance and more muscle strength than older people (Carty et al., 2011). Improvements in balance and muscle strength are the expected results of the Otago Exercise Programme (Campbell and Robertson, 2003). Therefore, group 2 simulated a group of people after practising the exercises. The existence of significant differences between both groups would suggest that those parameters could be used to distinguish people according to their physical conditions, and could also be used in the monitorization of people undergoing an exercise programme such as the Otago Exercise Programme.

Chapter 5

Results and discussion

In this work, a method to analyse functional gait exercises and calculate meaningful gait parameters was developed. The method was validated by comparing methodology's results to video's annotations of the data collection trials. Inter-group and intra-individual comparisons of the extracted gait parameters were also performed.

The results of the methodology validation and of the inter-group and intra-individual comparisons are presented in the following sections.

5.1 Validation results

The accuracy of the used method, when compared to the annotations of the videos, was quantified using the relative error, equation 5.1. In that equation, x_o represents the estimated measure, and x represents the real value. The relative error was computed for each value of each participant and, then averaged between all. Table 5.1 shows the mean errors and standard deviation in the determination of the gait parameters.

$$relative\ error = \frac{\| x_o - x \|}{\| x \|} \times 100 \tag{5.1}$$

Regarding the stride detection, two error values were calculated. Strides non-detected were the strides present in the ground truth but not detected by the proposed methodology. Strides over-detected were strides detected by the algorithm that should not have been detected according to the ground truth. A stride was considered correctly detected if the central time sample of its non-stationary phase was contained in the non-stationary phase of a stride in the ground truth. It was assured that each stride of the ground truth could only correspond to one stride detected by the algorithm. The remaining error values were only computed for strides correctly detected.

In general, stride detection was successful. 4 to 8% of the strides present in the ground-truth were not detected, and 1 to 2% of the detected strides should not have been detected. In an exercise of 20 strides, 8% (the highest error value) represents an absolute error of 1.6 strides, and 1% (the smallest value) represents an absolute error of 0.2 strides per repetition of the exercise. The non-detected strides usually happened before or after the turn which means they were being

Table 5.1: Mean errors and standard deviation in the determination of gait parameters.

Duration of non-stationary phase	SN	EN	Stride duration	Stride length	Stride non-detected	Stride over detected	Turn duration	Turn start	Turn end
Backwards walking exercise									
31 ± 10 %	1 ± 0,3 %	1 ± 0,05 %	6 ± 3 %	52 ± 15 %	4 ±4 %	1 ± 3%	35 ± 27%	2 ± 3%	3 ± 2%
Tandem walking exercise									
20 ± 7%	1 ± 0,3%	1 ± 0,3%	6 ± 2%	82 ± 26%	4 ± 3%	2 ± 4%	33 ± 22%	2 ± 3%	3 ± 3%
Tandem walking backwards exercise									
21 ± 7%	1 ± 0,3%	1 ± 0,3%	6 ± 2%	58 ± 17%	4 ± 5%	2 ± 3%	32 ± 20%	2 ±3%	3 ± 2%
Heel walking exercise									
38 ±11%	1 ± 0,3%	1 ± 0,04%	5 ± 4%	63 ± 10%	8 ± 5%	2 ± 4%	44 ± 37%	2 ± 2%	3 ± 3%
Toe walking exercise									
20 ± 6%	1 ± 0,3%	1 ± 0,3%	8 ± 4%	60 ± 16%	7 ± 6%	2 ± 2%	39 ± 56%	2 ± 2%	3 ± 3%

discarded as part of the turning movement. Therefore, improving turning detection (which has a considerable error in the duration estimation) could improve stride detection. Considering that the gait parameters later used to assess exercise performance are taken from the middle strides, mistakes in discarding strides due to the turning movement decrease the amount of information taken from the exercise. So, the correct detection of the strides and of the turning movement is highly desirable.

The over detected strides could also be related to errors in the turn detection (i.e. strides already belonging to the turning movement that were not discarded), or strides taken right before starting the exercise that are not from the exercise. For example, after being told to start, some participants took small steps to reach a more stable position before actually starting the exercise. Those strides were detected because the proposed stride detection method was based on characteristics present in the strides of all the exercises analysed, and did not differentiate between them. A future improvement should use the knowledge about the different exercises gathered in this work to include specific characteristics of the exercises, such as signals patterns and percentage of the GC in each phase, and discard strides that do not correspond to the exercise being analysed.

The determination of the turn start and the turn end was done with a mean relative error of 2 and 3%, respectively. The mean relative error in turn duration varied between 30 and 43%. Although the determination of the start and the end of the turn had small relative errors, those small errors have led to a significant relative error in the duration of the turn. In the presented method, the turn detection was based on the angular velocity around the vertical axis. In the annotation process, the turn start moment was when the foot started moving. At that moment, the acceleration signal increased but the angular velocity in the vertical axis only increased after. A similar process happened at the turn end. Therefore, the turn detection method may be improved by including data from the acceleration signal. The duration of the turn, its start and end were not parameters of interest to evaluate the exercise. Their estimation's purpose was to separate between the two parts of the exercise and discard any strides that could be detected in that period. Therefore, the accuracy in their estimation was not a significant concern during the method development. However, their estimation is affecting stride detection as described before and should be improved in the future.

The determination of the gait phase limits was performed with a mean relative error of 1% in all exercises. Stride duration was estimated with a relative error varying between 5% in the heel walking exercise and 8% in the toe walking exercise. The start, the end of the non-stationary phase and the stride duration were determined with a small relative error. In contrast, the relative error of the duration of the non-stationary phase was higher. This suggests that the determination of these gait parameters should be more accurate. Nevertheless, when analysing these error values, one must take into account that the ground truth was the annotation of a single video of the exercise, and as explained in section 4.11, the annotation process had some inaccuracies. For example, figure 5.1 shows the magnitude of the acceleration signal with the ground truth. In that figure, it is possible to observe that in some strides the ground truth annotations were set when the acceleration was still high, and the proposed method would only set the stride limits in areas of low acceleration variation, causing a significant error. Therefore, the use of, at least, another camera to record the exercises from another angle could provide more information regarding the accuracy of the estimated parameters.

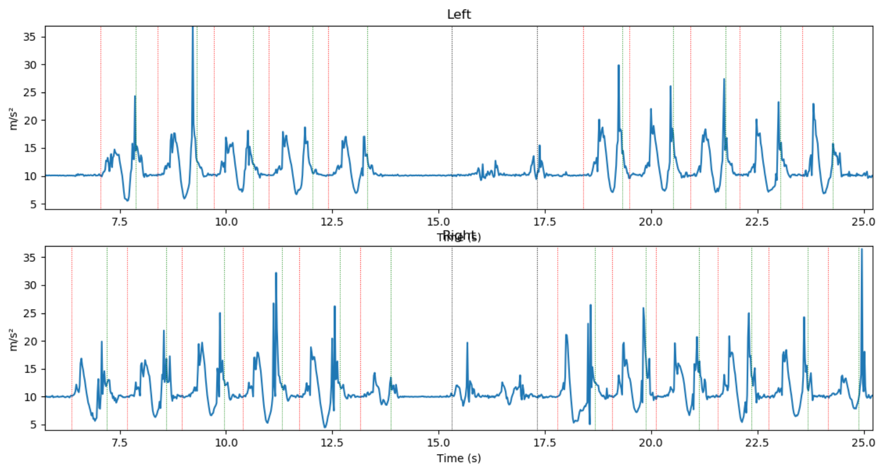


Figure 5.1: Magnitude of the acceleration signal with the ground truth. Red vertical lines represent the SN, green vertical lines represent EN, and black vertical lines indicate the start and the end of the turn.)

The stride length was the parameter with the highest mean relative error. It varied between 52 and 83%. These relative error values were considerable, and the determination of this parameter was not successful. There are several possible explanations for this result. The gravity component of the acceleration signal was removed based on the assumption that the orientation estimation is correct. However, when calculating the stride length in each direction, the same assumption was proved wrong, although the vertical direction seemed to be correctly estimated. So, a part of the gravity component may not have been removed and lead to the error in the stride length estimation. In addition, since it was not possible to estimate the stride length in each direction, the stride length was defined as the norm of the vector containing the displacement in two directions. The stride length in the ground truth is only the displacement in the longitudinal direction. Therefore, if a participant took a stride forward and to the side, the error will increase because different measures are being compared. Also, the integration limits and initial conditions were set based on the assumption that velocity can be considered zero in the stationary phase, as in Wang et al. (2013). When viewing the videos, that assumption was found to be wrong, specifically in the heel and toe walking exercises. Therefore, in the future, a strategy like the one proposed by Yang et al. (2013) should be implemented. Another possible source of error was integration drift caused by noise in data (Rampp et al., 2015; Kok et al., 2017). Due to the high value of error in the estimation of this parameter, stride length was not used in any of the inter-group and intra-individual comparisons.

As a final remark of the method validation, the relative error values were similar between exercises suggesting this methodology can be applied to all of them.

5.2 Inter-group comparisons

Table 5.2 presents the results of the inter-group comparisons using a one-way ANCOVA with velocity as the covariate. That velocity was calculated using the ground truth annotations because the errors in the stride length estimation prevented accurate velocity estimation.

Table 5.2: Inter-group comparisons results.

	Backwards walking		Tandem walking		Tandem walking backwards		Heel walking		Toe walking	
Parameter	Group1	Group2	Group1	Group2	Group1	Group2	Group1	Group2	Group1	Group2
SVA mean	16,67±3,67	17,46±2,09	**12,66±1,00***	**13,59±1,81***	13,35±1,49	13,52±2,11	**14,02±2,30***	**12,42±1,96***	18,06±2,56	18,61±2,19
SVA minimum	2,13±0,87	2,04±0,43	2,51±0,36	2,97±1,06	2,71±0,82	2,99±0,95	2,07±0,64	2,22±1,24	2,34±0,85	2,54±1,21
SVA maximum	42,27±8,71	42,23±5,36	35,68±3,21	37,49±6,97	37,76±5,16	36,37±7,75	**30,06±5,74***	**26,35±4,30***	45,72±6,17	46,44±6,37
SVA variance	156,75±73,52	142,31±46,63	79,83±20,70	89,51±44,20	102,99±36,22	98,62±52,30	**66,47±23,33***	**52,05±18,10***	151,26±47,75	161,15±43,10
Acceleration minimum	0,49±0,18	0,41±0,17	**0,23±0,05***	**0,19±0,03***	**0,43±0,13***	**0,28±0,07***	0,25±0,06	0,27±0,07	0,45±0,14	0,45±0,16
Acceleration maximum	**17,49±4,86***	**13,92±2,65***	**18,33±3,89***	**13,33±2,69***	**17,42±4,20***	**13,14±3,31***	**18,71±4,67***	**14,84±4,05***	**22,82±8,06***	**19,5±5,25***
Acceleration mean	**4,88±1,67***	**4,24±1,00***	**4,76±1,48***	**3,63±0,87***	4,27±1,44	3,35±1,03	**5,2±1,68***	**4,44±1,15***	6,32±2,38	5,93±1,65
Acceleration variance	**20,75±11,82***	**13,45±5,47***	**26,76±13,79***	**14,19±6,61***	19,15±10,51	11,37±6,84	**28,04±15,13***	**17,67±9,78***	**37,6±24,38***	**27,34±12,11***
Angular velocity minimum	0,34±0,12	0,37±0,10	0,16±0,05	0,16±0,08	0,2±0,10	0,14±0,039	**0,33±0,07***	**0,29±0,05***	0,33±0,15	0,35±0,09
Angular velocity maximum	4,62±1,13	4,19±0,82	4,89±0,89	4,36±0,75	4,12±0,68	3,5±0,69	**4,17±0,67***	**3,23±0,82***	5,15±1,01	4,9±0,73
Angular velocity mean	1,7±0,51	1,65±0,32	1,4±0,28	1,25±0,24	1,3±0,27	1,1±0,24	**1,48±0,29***	**1,28±0,31***	1,89±0,50	1,87±0,37
Angular velocity variance	1,58±0,74	1,25 ± 0,47	1,81±0,68	1,38±0,44	1,27±0,49	0,86±0,32	**1,26±0,38***	**0,79±0,44***	2,08±0,81	1,88±0,55
Stride mean	1,43±0,25	1,5±0,21	1,78±0,43	1,99±0,42	1,79±0,29	2,09±0,57	1,31±0,29	1,39±0,24	**1,22±0,26***	**1,34±0,26***
Stride CoV	12,36±11,02	7,73±7,45	**15,4±5,33***	**5,36±1,39***	13,98±9,68	8,96±6,08	**15,16±7,59***	**9,42±6,08***	22,14±21,89	13,1±17,42
Non-stationary phase mean	1,18±0,12	1,22±0,14	1,08±0,07	1,11±0,13	1,11±0,07	1,27±0,29	**1,04±0,08***	**1,18±0,12***	1,02±0,13	1,09±0,13
Non-stationary phase CoV	**7,91±3,10***	**5,86±2,69***	**9,03±3,86***	**7,47±2,56***	9,73±2,88	10,41±4,52	**9,67±4,78***	**6,13±3,53***	8,33±4,06	5,96±3,45
Non-stationary phase (% of GC)	80,96±11,22	80,89±7,752	**67,62±13,14***	**57,35±10,66***	66,36±10,89	61,65±8,81	84,85±12,86	88,09±6,39	81,45±12,48	82±13,06

* Significant difference for $p < 0,05$

Significant differences between groups were found in all the exercises but regarding different gait parameters. In the backwards walking exercise, significant differences were found in the maximum, mean and variance of the acceleration and variability of the non-stationary phase duration. All these parameters presented a higher value in group 1. In the tandem walking exercise, significant differences were found for the mean of SVA; minimum, maximum, mean and variance of acceleration; variability of stride time and of non-stationary phase time; and percentage of the GC spent in the non-stationary phase. Excluding SVA mean, all the parameters showed a higher value in group 1. In the tandem walking backwards exercise, only the minimum and the maximum of the acceleration signal showed a significant difference between groups. Both values were higher in the group 1. In the heel walking exercise, almost all gait parameters showed a significant difference between groups with higher values in the group 1. Only the SVA minimum, acceleration minimum, mean of stride time and percentage of GC spent in the non-stationary phase did not show a significant difference between groups. In the toe walking exercise, significant differences were found for maximum and variance of acceleration and stride time. Excluding stride time, the values of these parameters were also higher in group 1.

Minimum values of acceleration and angular velocity are found during the stationary phase. In this phase, the foot is placed on the floor, and it assumes a support and stability role. Maximum stability is gained by having the foot stationary and in complete contact with the floor (Bowker and Michael, 1992). Therefore, acceleration and angular velocity should be close to zero in this phase. Higher values can be associated with instability during that phase caused by incorrect foot placement or small movements to account for unbalances. So, the higher values in these parameters among the older group suggest that this group presented more difficulties in maintaining the equilibrium of the stationary phase in the tandem walking and tandem walking backwards exercises.

The maximum values of acceleration and angular velocity happen during the non-stationary phase, at moments such as the mid-swing and heel-strike. Higher values in these parameters may be associated with abrupt movements. Together with the values of mean and variance, the higher values of acceleration and angular velocity parameters in the group 1 suggest that these population presented a more variable and unsteady gait. These results are concordant with what is reported on literature about age-differences in gait (Kobsar et al., 2014; Zhang et al., 2011).

The SVA angle measures the angle between the vertical direction and the shank. This parameter is mostly measured in static conditions, and its variation during gait is not well studied which complicates its correct interpretation in this analysis (Owen, 2010). Starting from a standing position, the more the shank moves away from the support leg (and vertical direction), the more the SVA increases. Considering that SVA is similar to half of the angle used in biomechanical models-based approaches to compute stride length, the more the SVA increases, the bigger should be the stride length (Silva et al., 2017). Decreasing stride length is a usual strategy to deal with walking difficulties (Hamill et al., 2015) which may be associated with a smaller SVA. Having higher values of SVA mean, maximum and variance in the heel walking for the group 1 may seem contradictory because all the other parameters suggested that group 1 showed more walking difficulties in this exercise. However, the higher values of SVA parameters may also be the outcome of the walking instability leading to a higher value of SVA but in an uncontrolled manner. For example, a person that loses balance may take a bigger stride to avoid falling. Since it was not possible to accurately estimate stride length and the exercises were recorded in the frontal plane, this hypothesis could not be studied in detail in this work.

The higher values of variability in stride time and non-stationary phase duration among the older group were also in agreement with the literature. Other works that studied forward gait also reported a higher variability among older populations that may be related to a decline in control and coordination of the locomotor system (Kobsar et al., 2014; Zhang et al., 2011).

In the tandem walking exercise, the percentage of GC spent in the non-stationary phase also presented a significant difference between groups. Considering that there is no significant difference in stride time or in the non-stationary phase time, this result suggested that the older group showed more difficulties in placing their foot in a position stable enough to support the body weight while the opposite foot was in the air.

The gait parameters showing significant differences between groups have varied between exercises suggesting that some exercises may be easier than others and that different exercises may expose different weaknesses. For example, while in daily life some situations force people to walk on toes (i.e. using high heels, avoiding obstacles, trying to walk without noise), there are no situations when people walk on heels. Therefore, it is normal that, when confronted with a new exercise, younger people were more comfortable and had a more stable gait because they can recover more easily from unbalancing situations (Carty et al., 2011).

During data acquisition, it was clear that tandem walking backwards was the most challenging exercise because it was the one where more people have lost their balance and more times in both groups. The fact that there were almost no parameters with significant differences between groups is not surprising considering that this exercise is only prescribed in the later stages of the Otago Exercise Programme (Campbell and Robertson, 2003) to people who already can do it safely possibly as the group 1 members. These participants were healthy adults, and most of them did not report any walking difficulties.

5.3 Intra-individual analysis

Intra-individual analysis refers to the comparison of gait parameters between both limbs of the same person; therefore, it is an indicator of gait symmetry, and it was performed as described in section 4.9.

Table 5.3 presents the results of intra-individual comparisons for participants 3, 8, 23 and 24 in all exercises. These participants were considered a representative sample of their groups. Participants 3 and 8 belonged to group 1 while participants 23 and 24 were members of group 2. Also, participant 8 reported right limb impairments, and participant 24 reported left limb impairments. The entire results for all participants are presented in the appendix A.

Table 5.3: Intra-individual comparisons for participants 3, 8, 23 and 24 in all exercises. L and R identify the mean values of the left and right limb, respectively.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Anguar velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
Backwards walking exercise																
3	L	0,56	12,99	4,64	11,36	0,38	5,02*	1,95	1,79*	2,29	54,00	21,66	272,10	1,40*	1,62	88,50
	R	0,62	15,24	4,73	13,53	0,41	4,28*	1,85	1,46*	2,82	50,75	20,90	206,34	1,42*	1,59	89,43
8	L	0,25*	13,74	2,81	9,15	0,31	2,82	1,10	0,55	2,78	30,93*	13,62	54,41*	1,38*	1,66	80,25*
	R	0,37*	13,28	2,84	9,06	0,29	2,81	1,15	0,65	3,36	36,45*	13,45	94,88*	1,24*	1,65	74,84*
23	L	0,26	12,11	3,11	7,68	0,27	3,14	1,32	0,73	2,48*	40,97	17,60	124,28	1,54	2,04	75,53
	R	0,25	12,74	3,23	8,32	0,24	2,98	1,29	0,71	1,60*	39,35	16,43	125,70	1,46	1,94	74,27
24	L	0,44*	10,66	3,54*	8,59	0,31	4,56*	1,65*	1,49*	1,64	50,49	19,07*	205,13	1,17	1,69	70,06
	R	0,32*	10,16	3,31*	7,09	0,30	4,05*	1,56*	1,10*	1,24	48,81	17,85*	206,10	1,24	1,26	74,60
Tandem walking exercise																
3	L	0,27	17,31*	5,01	20,96*	0,21	3,99*	1,41*	1,36*	2,42*	39,34	14,30	108,04	1,20	1,60	81,13
	R	0,22	20,53*	5,56	29,56*	0,16	4,71*	1,59*	1,83*	3,60*	37,87	13,70	84,97	1,17	1,75	79,33
8	L	0,22*	10,77	2,01	5,24	0,11	3,51	0,89	0,75	2,14	32,21	13,02*	43,87	1,17	2,81	45,40
	R	0,16*	10,54	2,06	5,54	0,09	3,23	0,83	0,66	1,79	35,07	11,60*	63,81	1,03	2,69	41,52
23	L	0,19*	14,16	2,46*	6,73	0,07	3,01	0,81	0,68	2,53	32,72*	11,09	55,88*	1,31	2,90	44,68
	R	0,08*	12,36	2,20*	6,53	0,06	2,83	0,75	0,62	1,44	27,53*	11,98	32,13*	1,31	2,91	45,10
24	L	0,23	10,30*	2,93*	8,49*	0,08	4,12*	1,09*	1,45*	3,81	57,01*	15,01	241,52*	1,07	2,36	46,32
	R	0,19	8,74*	2,61*	6,12*	0,11	3,74*	1,00*	1,05*	3,46	49,70*	15,42	169,95*	1,08	2,36	46,02
Tandem walking backwards exercise																
3	L	0,57	16,04	4,15	14,97	0,20	4,19	1,31	1,21	12,48	2,74	37,60*	98,61*	1,20	2,04	66,43
	R	0,36	17,06	4,13	16,52	0,18	3,74	1,24	1,02	11,83	3,86	34,85*	71,67*	1,15	1,98	66,77
8	L	0,35*	13,20	2,82	8,10*	0,27	2,87	1,16	0,61	13,82	3,27	30,31*	54,90*	1,34*	1,80	79,93*
	R	0,27*	14,23	2,84	9,55*	0,31	2,70	1,17	0,62	13,81	3,91	36,33*	85,42*	1,18*	1,70	71,50*
23	L	0,17	9,68	1,60	2,87	0,06	2,18	0,55*	0,26	11,02*	4,48*	25,82*	28,46	2,24	3,98	51,12
	R	0,13	10,33	1,54	3,23*	0,05	1,98	0,47*	0,19	9,02*	3,24*	21,81*	24,70	1,83	3,67	44,04
24	L	0,35*	11,62	3,01*	6,73*	0,09	3,05	1,08	0,75	14,50	2,57	46,96	165,89*	1,36	2,16	62,57
	R	0,24*	9,10	2,70*	4,90*	0,12	3,23	1,09	0,72	15,25	3,06	48,16	185,67*	1,35	2,17	60,78
Heel walking exercise																
3	L	0,32	22,74	6,62	33,96	0,46*	3,99	1,65	1,12	1,73	26,02*	11,58*	50,41*	0,99	1,13	95,90
	R	0,38	23,52	6,57	34,46	0,39*	3,77	1,58	0,97	2,18	32,62*	14,58*	79,57*	1,04	1,16	96,06
8	L	0,27*	10,19*	2,79	8,57*	0,28	2,80	0,97	0,50	1,64	21,61	10,86*	31,55*	1,05	1,43	76,88
	R	0,20*	13,32*	3,12	12,67*	0,25	3,11	1,05	0,72	1,02	21,91	9,96*	38,41*	1,07	1,39	78,72
23	L	0,37	13,76	3,87	10,90	0,18	2,56	1,05	0,42	6,10	31,35	15,54*	60,65	1,29	1,84	79,50
	R	0,30	13,63	3,71	10,24	0,24	2,41	0,99	0,39	5,72	33,24	16,89	74,24	1,36	1,83	80,85
24	L	0,42*	19,45*	5,67	28,18*	0,37	3,19	1,51*	0,83*	5,04*	30,38*	15,63*	54,17*	1,10	1,20	95,38*
	R	0,32*	14,92*	5,31	19,48*	0,32	3,01	1,37*	0,63*	2,71*	25,37*	11,91*	46,94*	1,13	1,13	97,87*
Toe walking exercise																
3	L	0,70	39,94	10,07	85,61	0,55	6,58*	2,62	3,03*	3,14	46,91	19,90	164,34	0,77	0,98	85,77
	R	0,70	42,07	10,05	94,92	0,61	6,06*	2,53	2,56*	2,89	49,03	20,28	164,05	0,75	0,98	82,15
8	L	0,21	11,38*	2,91*	7,64*	0,28*	3,86*	1,28*	0,99*	1,05	38,80*	15,76*	81,73*	1,07*	1,61	67,38*
	R	0,30	14,07*	3,23*	13,21*	0,22*	4,17*	1,23*	1,20*	1,30	41,13*	14,96*	107,88*	0,91*	1,58	55,84*
23	L	0,48	27,75	5,97	38,55	0,35	4,19	1,69	1,47	1,36	42,99	15,54	156,11	1,08	1,41	80,68
	R	0,49	27,51	6,24	43,11	0,27	4,41	1,66	1,66	1,28	44,85	15,91	163,60	1,09	1,39	83,16
24	L	0,53	26,38*	8,20*	50,29*	0,39	5,79*	2,25*	2,83*	3,61*	60,42*	23,85*	283,46*	1,07*	1,19	92,24*
	R	0,44	20,30*	6,90*	29,87*	0,34	4,56*	1,94*	1,75*	1,59*	48,20*	18,67*	175,59*	1,13*	1,22	95,95*

* Significant difference for p<0,05

All the participants showed significant differences for some of the gait parameters. This was expected because perfect gait symmetry is not usual. A healthy individual presents minor deviations from gait symmetry between dominant and non-dominant limbs (Sadeghi, 2003). Besides, for each participant, the gait parameters showing significant differences were not constant in all exercises. This suggested that different exercises may expose different weaknesses which can be related with the fact that different exercises use different muscles, and the force distribution among them is also different (Flynn and Soutas-Little, 1993). Both these results support the hypothesis that the analysis of different types of gait can provide more information regarding walking impairments.

Participants 8 and 24 were the ones showing significant differences between limbs in more gait parameters. Among the parameters showing significant differences, higher values corresponded to the impaired limb. The gait parameters compared between both limbs are similar to the ones used in the inter-group comparison, and, therefore, their interpretation is similar.

Higher values of the minimum of acceleration and angular velocity in one limb suggested that the person had difficulties in maintaining equilibrium and supporting body weight in that limb during the stationary phase. Higher values of maximum, mean and variance of acceleration and angular velocity in one of the limbs also suggested that that limbs' movements were more abrupt and variable which could be corroborated with the visualization of the video-recordings.

In the intra-individual analysis, the SVA parameters were easier to interpret. The maximum SVA happened during the non-stationary phase when the body weight was being supported by the opposite limb. In participants 8 and 24, the limb with higher maximum and mean values was the impaired limb. This suggested that the healthy limb was more stable in the stationary phase, and allowed a larger range of motion of the other limb during gait. Therefore, the SVA could also be an indicator of walking impairments.

Regarding the temporal parameters, walking impairments in one limb seemed to be related to a smaller non-stationary phase and a smaller percentage of the gait cycle spent in that phase. This was not in agreement with what is reported in the literature about gait asymmetries. Usually, the impaired limb is associated with a larger swing time and a smaller stance time (Chen et al., 2005; Titianova et al., 2003). However, the swing phase definition usually used in the literature is different from the non-stationary phase used in this work, and the comparison between both may not be correct. Therefore, future improvements of this work should include the stride segmentation into more phases. This would not only enable the comparison of results with other works but also provide more information about gait.

In gait analysis, comparison of results between studies is usually difficult due to the use of different sensors, gait parameters, statistical measures, populations of interest and experimental protocols. Taking into consideration that examples of gait analysis in functional gait exercises are scarce, the comparison of results of this work with the available literature was even more complicated. Therefore, data acquisition from a bigger sample including healthy young and older people and also people with impaired gait could be used to confirm the obtained results.

Chapter 6

Conclusions and Future Work

As the elderly population grows, concerns related to health conditions and quality of life of this age group increase. Falling has been proved to be a significant cause of morbidity and mortality in the elderly, and its prevention represents an important field of intervention. In this area, gait analysis represents a possibility to assess fall risk, which may help to define prevention strategies. Being aware of the limitations of the previous works on gait analysis, in this work, gait analysis was performed on functional gait exercises selected from the Otago Exercise Programme using data collected with IMUs.

The used methodology evaluated five exercises: backwards walking, tandem walking, tandem walking backwards, heel walking and toe walking. Gait parameters such as the number of strides, stride time, stride length and turn duration were computed. Data were collected from 14 older adults and 14 young adults, and the validation of the developed method was done by comparing the estimated parameters to the video-recordings of participants performing the exercises.

The number of strides was determined with a maximum relative error of 8%. The start and the end of the two identified gait phases were estimated with a 1% error; however, the stride time and non-stationary phase time had higher error values. Turn duration was determined with a relative error varying between 30 and 43%. Stride length estimation was not successful as the relative error achieved a maximum value of 83%. In general, stride detection and segmentation were successful; however, both stride length estimation and turn detection should be improved.

Gait parameters, such as the stride time and its variability, maximum and minimum values of acceleration, angular velocity and SVA, were compared between the two groups of participants for each of the exercises. Significant differences between groups were found in all of the exercises suggesting that those parameters could be used to monitor and measure the exercises' effects on people undergoing exercise programmes. The gait parameters showing significant differences between groups varied among the exercises. This suggests that some exercises may be easier than others and that different exercises may expose different weaknesses.

Intra-individual comparisons of gait parameters similar to the ones compared between groups were also performed. All participants showed significant differences in some gait parameters in, at least, one of the exercises. For each person, the gait parameters showing significant differences were not the same in all exercises also suggesting that different exercises can expose different weaknesses. The participants that reported impairments in one of the limbs were the ones showing more gait parameters with significant differences, which suggests that those gait parameters could be used to evaluate the success of the exercise programme. Also, higher values in gait parameters, such as the minimum and the maximum of acceleration, were associated with the impaired limb which suggests that impairments in one of the limbs could be identified with the presented methodology.

Future developments of this work may include improvements in the turn detection which would enhance stride detection. Stride length estimation could be improved by enhancing the orientation estimation algorithm or by developing a proper calibration method. Accuracy in the determination of temporal parameters could be better assessed by using a commercially available motion tracking system. Additionally, the knowledge gathered regarding the signals' patterns and the sequence of gait events in each of the exercises could be used to segment each stride into more gait phases and gain more useful information.

The hypothesis that different exercises could expose different issues and provide more information to healthcare professionals could be better investigated by collecting data of forward gait. It would also be important to collaborate with healthcare specialists to better interpret the obtained results and their possible application in clinical practice.

Moreover, bigger samples including not only healthy young people and seniors but also people with impaired gait should be used to confirm the obtained results and justify this method application in clinical practice. The suggested improvements may provide a more robust method to analyse gait which would, ultimately, be helpful in fall prevention. Also, regular data acquisition during the execution of an exercise programme would help to understand if the computed gait parameters can be used to track improvements in balance and strength.

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Appendix A

Intra-individual comparisons

A.1 Backwards walking exercise

Table A.1: Intra-individual comparisons in the backwards walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
1	L	0,64	15,89	4,87	16,35	0,28	4,91	1,66	1,66	0,88	46,05	16,36	**202,85***	1,23	1,48	83,52
	R	0,67	16,57	4,85	15,86	0,18	4,40	1,59	1,47	2,76	42,68	15,39	**156,07***	1,28	1,45	85,36
2	L	0,38	12,27	**2,83***	8,12	0,21	**3,91***	**1,22***	**1,00***	1,72	**43,00***	16,12	**140,80***	1,20	1,73	67,77
	R	0,45	12,42	**3,13***	8,54	0,19	**4,34***	**1,30***	**1,28***	1,91	**48,37***	16,72	**214,80***	1,14	1,71	64,78
3	L	0,56	12,99	4,64	11,36	0,38	**5,02***	1,95	**1,79***	2,29	54,00	21,66	272,10	**1,40***	1,62	88,50
	R	0,62	15,24	4,73	13,53	0,41	**4,28***	1,85	**1,46***	2,82	50,75	20,90	206,34	**1,42***	1,59	89,43
4	L	0,89	24,44	7,53	34,39	0,54	6,32	2,59	2,91	1,39	54,33	21,39	279,87	1,24	0,97	92,57
	R	0,56	23,10	8,04	37,34	0,45	6,51	2,53	2,94	1,12	55,74	21,77	281,21	1,29	1,34	96,02
5	L	**0,59***	16,49	4,74	17,19	0,46	4,75	1,71	1,34	1,88	41,37	17,28	143,25	1,19	1,38	85,30
	R	**0,29***	15,03	4,52	15,39	0,39	4,71	1,80	1,43	2,23	41,04	17,51	135,23	1,21	1,35	86,26

Table A.1: Intra-individual comparisons in the backwards walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
6	L	0,47	20,01	6,37	29,12	0,49	5,46	2,17	2,01	2,05	47,67	20,51	208,19	1,26	1,18	85,34
	R	0,51	20,72	6,31	29,73	0,39	5,22	2,04	1,91	1,78	45,29	19,70	183,37	1,22	1,29	82,00
7	L	0,39	14,38	4,75	16,33	0,40	**4,84***	1,87	**1,78***	**1,88***	**38,90***	**17,51***	101,83	1,05	1,26	81,60
	R	0,38	14,74	4,69	14,62	0,46	**5,24***	1,94	**1,90***	**7,48***	**42,49***	**19,59***	109,07	1,05	1,26	82,85
8	L	**0,25***	13,74	2,81	9,15	0,31	2,82	1,10	0,55	2,78	**30,93***	13,62	**54,41***	**1,38***	1,66	**80,25***
	R	**0,37***	13,28	2,84	9,06	0,29	2,81	1,15	0,65	3,36	**36,45***	13,45	**94,88***	**1,24***	1,65	**74,84***
9	L	0,28	11,19	2,35	6,98	**0,20***	**2,97***	**0,97***	0,58	1,64	**29,01***	**11,17***	**61,75***	1,13	1,69	65,08
	R	0,30	11,06	2,54	8,18	**0,09***	**2,28***	**0,76***	0,41	1,02	**22,29***	**8,13***	**38,37***	1,11	1,72	65,45
10,00	L	**0,49***	17,72	5,74	25,16	0,35	5,17	**2,05***	**2,11***	2,20	**42,71***	**17,61***	**154,84***	1,20	1,27	91,08
	R	**0,30***	18,00	5,77	25,21	0,40	4,93	**1,88***	**1,68***	1,33	**37,19***	**16,26***	**120,09***	1,15	1,26	90,99
11,00	L	0,24	**17,95***	3,58	21,67	**0,18***	4,78	1,17	1,39	2,31	37,94	13,81	93,73	**0,92***	1,87	53,23
	R	0,25	**14,73***	3,28	15,36	**0,27***	4,48	1,18	1,23	2,20	38,37	13,52	100,16	**1,02***	1,85	59,50
12,00	L	0,49	**16,23***	4,23	**16,44***	0,21	**3,11***	**1,12***	**0,62***	1,89	**26,44***	**10,15***	**50,71***	**1,23***	1,44	**85,02**
	R	0,46	**20,44***	4,21	**20,41***	0,26	**3,57***	**1,25***	**0,80***	1,54	**32,09***	**11,94***	**85,98***	**1,07***	1,44	**73,53**
13,00	L	0,85	**30,60***	7,38	51,95	0,42	6,10	2,29	2,67	**1,17***	51,47	19,16	259,44	0,98	1,10	85,15
	R	0,89	**26,21***	7,28	42,86	0,44	6,51	2,33	2,93	**2,26***	52,85	19,73	250,68	1,02	0,86	88,50
14,00	L	0,63	21,38	5,98	28,82	**0,41***	**4,71***	1,88	1,65	1,98	46,07	17,06	179,17	1,17	1,29	90,02
	R	0,62	21,80	6,07	27,64	**0,53***	**5,07***	2,00	1,85	1,72	44,62	17,50	174,80	1,15	1,27	89,90
15,00	L	0,32	10,98	3,65	8,37	0,42	**4,23***	**1,59***	**1,14***	1,35	43,22	18,28	141,00	**1,27***	1,56	79,40
	R	0,43	10,15	3,75	7,98	0,32	**4,51***	**1,68***	**1,29***	1,48	43,03	18,63	143,63	**1,21***	1,55	77,50
16,00	L	0,43	11,82	**3,07***	8,05	**0,28***	**3,74***	1,30	1,06	**2,91***	40,79	**15,61***	118,84	1,09	1,70	64,31
	R	0,33	11,57	**2,84***	8,01	**0,24***	**3,39***	1,26	0,99	**1,33***	40,10	**14,79***	109,44	1,07	1,68	63,74
17,00	L	0,34	16,10	4,97	**17,09***	0,47	**4,47***	1,87	**1,19***	1,83	**44,66***	19,15	**176,27***	1,21	**1,31***	93,83
	R	0,37	17,10	4,97	**19,20***	0,45	**4,76***	1,88	**1,38***	2,75	**41,98***	18,37	**140,61***	1,23	**1,29***	94,08
18,00	L	0,49	16,80	**5,32***	20,10	**0,56***	4,30	2,03	**1,18***	**1,34***	**47,28***	**20,12***	**183,84***	1,26	1,41	87,30
	R	0,55	17,69	**5,67***	21,09	**0,33***	4,32	2,13	**1,59***	**2,24***	**41,04***	**18,78***	**128,86***	1,26	1,38	88,17
19,00	L	0,68	16,54	5,13	19,42	0,44	**4,74***	**1,85***	1,84	2,48	40,47	17,40	124,34	1,06	1,26	82,96
	R	0,59	15,97	4,84	16,61	0,46	**5,14***	**1,99***	1,92	2,19	41,33	18,38	120,35	1,06	1,29	82,69
20,00	L	0,83	**16,62***	6,10	**22,16***	0,61	**6,47***	2,28	**2,55***	1,58	**54,51***	22,25	**250,49***	1,06	1,37	81,80
	R	0,95	**14,66***	5,86	**16,71***	0,54	**5,76***	2,19	**2,09***	1,66	**49,35***	21,59	**196,20***	1,11	1,39	82,73
21,00	L	0,26	17,11	4,40	18,50	**0,44***	4,50	1,59	1,31	2,53	38,41	**15,27***	118,45	**1,12***	1,33	**81,99**
	R	0,31	16,89	4,59	18,31	**0,36***	4,35	1,59	1,34	3,18	37,04	**14,03***	107,04	**1,19***	1,33	**87,60**

Table A.1: Intra-individual comparisons in the backwards walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
22,00	L	0,32	12,37	3,99	11,46	0,22	3,72	**1,36***	0,88	1,65	**35,50***	16,70	**83,90***	1,34	1,57	84,76
	R	0,29	12,33	3,84	9,00	0,28	3,77	**1,45***	0,91	1,29	**40,54***	17,16	**113,18***	1,34	1,57	84,18
23,00	L	0,26	12,11	3,11	7,68	0,27	3,14	1,32	0,73	**2,48***	40,97	17,60	124,28	1,54	2,04	75,53
	R	0,25	12,74	3,23	8,32	0,24	2,98	1,29	0,71	**1,60***	39,35	16,43	125,70	1,46	1,94	74,27
24,00	L	**0,44***	10,66	**3,54***	8,59	0,31	**4,56***	**1,65***	**1,49***	1,64	50,49	**19,07***	205,13	1,17	1,69	70,06
	R	**0,32***	10,16	**3,31***	7,09	0,30	**4,05***	**1,56***	**1,10***	1,24	48,81	**17,85***	206,10	1,24	1,26	74,60
25,00	L	0,30	13,11	**3,86***	11,69	0,34	3,26	1,37	**0,69***	**3,04***	**31,56***	**13,73***	76,97	1,35	1,52	**88,85**
	R	0,25	13,01	**4,15***	12,45	0,36	3,42	1,41	**0,81***	**1,44***	**36,07***	**15,62***	94,38	1,28	1,52	**83,82**
26,00	L	0,41	13,68	3,73	12,75	0,31	3,89	1,46	1,15	2,58	41,12	15,91	126,38	1,10	1,58	72,08
	R	0,47	12,93	3,58	10,33	0,29	3,74	1,47	1,02	2,30	39,95	15,63	117,97	1,13	1,54	71,93
27,00	L	**0,34***	11,43	3,20	7,15	0,28	3,36	1,33	**0,75***	2,18	**39,05***	**16,55***	102,38	1,44	1,73	**77,93**
	R	**0,23***	10,79	3,18	7,19	0,35	3,06	1,28	**0,57***	2,08	**35,97***	**15,69***	103,00	1,49	1,75	**86,65**
28,00	L	0,54	**16,50***	**5,34***	**18,86***	0,51	**4,78***	**1,95***	**1,53***	2,58	50,88	19,63	229,23	1,10	1,26	85,93
	R	0,35	**18,05***	**5,66***	**22,39***	0,36	**5,02***	**2,01***	**1,76***	2,24	51,27	19,17	234,47	1,08	1,28	85,95

* Significant difference for $p < 0,05$

A.2 Tandem walking exercise

Table A.2: Intra-individual comparisons in the tandem walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Anguar velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
1	L	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	R	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2	L	0,20	22,63	5,19	36,79	0,18	5,78	1,57	2,53	**1,35***	**45,69***	13,30	**153,74***	1,00	1,73	67,02
	R	0,25	22,61	5,16	36,89	0,12	5,49	1,52	2,34	**3,01***	**35,87***	12,98	**81,83***	1,00	1,61	68,89

Table A.2: Intra-individual comparisons in the tandem walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Anguar velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
3	L	0,27	**17,31***	5,01	**20,96***	0,21	**3,99***	**1,41***	**1,36***	**2,42***	39,34	14,30	108,04	1,20	1,60	81,13
	R	0,22	**20,53***	5,56	**29,56***	0,16	**4,71***	**1,59***	**1,83***	**3,60***	37,87	13,70	84,97	1,17	1,75	79,33
4	L	**0,35***	21,78	6,56	43,85	0,14	**5,66***	1,60	2,55	3,11	**38,33***	12,63	92,42	1,09	1,64	74,69
	R	**0,23***	22,25	6,72	46,66	0,12	**6,28***	1,66	3,04	2,60	**41,56***	13,51	99,20	1,10	1,59	75,26
5	L	**0,25***	16,30	**3,88***	**18,16***	0,20	4,38	1,22	1,31	2,52	33,42	12,38	72,79	1,11	1,96	65,03
	R	**0,18***	13,26	**3,37***	**12,63***	0,15	4,04	1,15	1,12	2,79	28,10	11,20	47,76	1,21	1,92	65,89
6	L	**0,28***	19,75	5,03	29,43	0,14	5,47	1,43	2,16	2,55	39,30	12,92	94,96	1,10	1,95	62,39
	R	**0,19***	18,80	5,09	26,21	0,14	5,63	1,46	2,23	3,43	36,99	12,21	79,76	1,13	1,92	64,46
7	L	0,22	16,06	3,77	18,79	0,08	4,84	1,15	1,45	2,46	32,96	11,67	**67,62***	1,08	2,22	52,42
	R	0,17	18,14	3,63	17,29	0,08	4,49	1,11	1,32	1,52	31,27	12,07	**40,62***	1,13	2,16	52,85
8	L	**0,22***	10,77	2,01	5,24	0,11	3,51	0,89	0,75	2,14	32,21	**13,02***	43,87	1,17	2,81	45,40
	R	**0,16***	10,54	2,06	5,54	0,09	3,23	0,83	0,66	1,79	35,07	**11,60***	63,81	1,03	2,69	41,52
9	L	0,20	14,84	3,37	13,60	0,16	**3,99***	1,25	1,11	2,66	**35,83***	**13,68***	**87,72***	**0,92***	1,58	**59,92**
	R	0,21	13,68	3,75	13,39	0,21	**3,39***	1,28	0,97	2,18	**30,75***	**12,18***	**63,35***	**1,12***	1,48	**74,24**
10	L	0,21	22,40	6,30	43,80	0,20	**5,03***	**1,57***	**1,98***	2,84	35,78	**13,73***	67,67	**1,04***	1,26	81,79
	R	0,25	20,98	6,36	41,22	0,21	**5,84***	**1,67***	**2,37***	2,26	32,10	**13,13***	54,30	**1,01***	1,39	80,68
11	L	0,18	13,87	**3,26***	13,68	**0,18***	**4,57***	1,26	1,42	2,07	36,84	12,48	93,97	0,98	1,72	58,63
	R	0,17	17,96	**3,67***	20,96	**0,25***	**5,40***	1,26	1,75	2,13	34,68	12,53	77,11	0,93	1,77	56,55
12	L	0,21	17,60	3,88	17,89	**0,07***	**4,55***	**1,11***	**1,46***	2,64	**33,03***	9,84	**61,32***	1,14	2,20	55,23
	R	0,16	18,25	4,06	20,65	**0,10***	**4,94***	**1,28***	**1,89***	2,25	**40,35***	10,46	**88,51***	1,12	2,15	54,75
13	L	0,30	24,54	6,90	49,73	0,18	6,26	1,93	2,95	2,49	36,78	12,94	100,54	0,95	1,21	83,16
	R	0,35	25,02	7,14	54,31	0,21	6,60	1,87	3,17	2,54	37,78	12,54	109,25	0,96	1,17	81,97
14	L	**0,37***	17,19	**5,70***	**24,74***	0,27	4,59	1,73	1,70	3,00	33,94	13,59	70,69	1,10	1,34	88,37
	R	**0,25***	19,54	**6,10***	**32,59***	0,23	4,46	1,68	1,77	2,73	31,04	14,25	61,44	1,13	1,38	86,26
15	L	0,25	12,19	**3,60***	**11,06***	0,36	**4,74***	1,54	1,65	3,80	45,27	**17,28***	**140,83***	0,91	1,72	54,71
	R	0,21	12,95	**3,89***	**14,42***	0,37	**4,95***	1,57	1,75	3,86	43,08	**16,29***	**120,67***	0,92	1,69	54,00
16	L	0,23	11,68	3,29	10,82	**0,18***	3,77	**1,21***	1,11	**3,25***	**40,23***	13,07	**108,66***	1,07	1,90	56,86
	R	0,17	11,65	3,21	9,80	**0,27***	4,03	**1,28***	1,12	**3,98***	**36,46***	13,79	**80,88***	1,05	1,91	55,16
17	L	0,15	10,84	2,70	7,95	**0,09***	4,30	1,03	1,14	1,72	38,18	12,06	89,90	0,94	2,19	44,21
	R	0,14	10,60	2,62	8,16	**0,14***	4,53	1,04	1,23	1,48	38,03	11,72	88,14	0,90	2,17	40,53
18	L	0,19	**18,39***	**4,49***	**22,97***	0,13	**4,71***	**1,30***	1,57	3,58	29,68	12,90	37,41	1,17	1,88	**61,27**

Table A.2: Intra-individual comparisons in the tandem walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Anguar velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
	R	0,17	**14,84***	**4,04***	**19,15***	0,11	**3,77***	**1,10***	1,12	2,73	26,52	13,30	31,45	1,08	1,91	**56,77**
19	L	**0,25***	12,09	**2,98***	**11,45***	**0,12***	**4,53***	**1,14***	**1,43***	**2,01***	**42,72***	**12,10***	**123,51***	1,00	2,22	45,41
	R	**0,15***	11,13	**2,73***	**9,56***	**0,18***	**3,87***	**1,07***	**1,08***	**3,29***	**34,60***	**13,88***	**53,48***	1,10	2,21	48,81
20	L	**0,23***	12,94	3,65	14,27	0,10	4,70	1,28	1,57	2,56	**40,35***	12,84	104,96	1,13	1,96	57,02
	R	**0,15***	12,67	3,51	13,82	0,10	4,46	1,27	1,66	3,41	**42,90***	13,51	116,04	1,18	1,98	58,66
21	L	0,19	17,45	5,41	24,61	0,19	5,40	1,70	2,08	3,50	**39,89***	13,19	**115,17***	1,08	1,40	78,08
	R	0,19	19,36	5,23	29,79	0,27	5,77	1,60	2,05	3,83	**35,01***	12,48	**74,36***	0,97	1,43	70,29
22	L	**0,24***	**11,72***	3,90	**12,29***	**0,16***	**3,66***	1,26	0,92	**1,12***	31,14	**11,67***	**59,27***	1,26	1,56	80,30
	R	**0,16***	**10,30***	3,82	**9,95***	**0,28***	**4,00***	1,32	0,98	**5,37***	28,69	**16,26***	**31,07***	1,17	1,57	75,54
23	L	**0,19***	14,16	**2,46***	6,73	0,07	3,01	0,81	0,68	2,53	**32,72***	11,09	**55,88***	1,31	2,90	44,68
	R	**0,08***	12,36	**2,20***	6,53	0,06	2,83	0,75	0,62	1,44	**27,53***	11,98	**32,13***	1,31	2,91	45,10
24	L	0,23	**10,30***	**2,93***	**8,49***	0,08	**4,12***	**1,09***	**1,45***	3,81	**57,01***	15,01	**241,52***	1,07	2,36	46,32
	R	0,19	**8,74***	**2,61***	**6,12***	0,11	**3,74***	**1,00***	**1,05***	3,46	**49,70***	15,42	**169,95***	1,08	2,36	46,02
25	L	0,18	**13,65***	4,01	15,99	**0,14***	**3,66***	1,20	1,13	1,78	**26,38***	**8,19***	**47,00***	1,09	1,55	**70,15**
	R	0,19	**12,59***	3,92	14,43	**0,22***	**4,11***	1,24	1,02	2,02	**28,92***	**12,64***	**34,83***	1,04	1,57	**65,90**
26	L	0,16	15,80	**4,37***	**20,68***	**0,12***	**5,19***	**1,47***	**2,09***	4,65	**44,84***	**16,93***	**115,03***	1,30	2,21	59,70
	R	0,12	19,51	**4,87***	**28,19***	**0,08***	**5,88***	**1,54***	**2,34***	6,11	**38,32***	**15,99***	**76,17***	1,28	2,23	59,09
27	L	0,20	**10,90***	2,94	9,08	0,07	3,91	1,06	1,05	2,30	36,86	13,65	**64,21***	1,21	2,41	**50,32**
	R	0,18	**13,38***	3,03	9,68	0,10	3,94	1,11	1,05	2,42	38,60	12,93	**94,74***	1,33	2,40	**57,26**
28	L	0,25	**15,80***	4,52	20,26	0,22	**5,50***	1,47	1,83	1,66	**35,12***	**17,52***	**65,36***	0,98	1,62	57,91
	R	0,18	**14,99***	4,61	20,70	0,24	**5,05***	1,45	1,74	1,29	**41,04***	**12,61***	**130,15***	1,02	1,61	63,94

* Significant difference for $p < 0,05$

A.3 Tandem walking backwards exercise

Table A.3: Intra-individual comparisons in the tandem walking backwards exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
1	L	0,47	**21,76***	**6,00***	**31,96***	0,14	5,08	1,56	2,36	14,25	3,31	47,56	187,05	1,17	1,60	79,62
	R	0,67	**27,77***	**7,53***	**44,30***	0,24	5,45	1,78	2,58	15,55	1,99	51,54	196,88	1,13	1,63	74,00
2	L	0,38	15,11	4,25	15,65	0,16	**4,05***	**1,36***	**1,27***	15,53	1,97	42,23	133,04	**1,13***	1,51	76,12
	R	0,66	16,58	4,60	17,54	0,18	**4,72***	**1,51***	**1,78***	14,22	1,54	42,66	137,56	**1,01***	1,49	68,43
3	L	0,57	16,04	4,15	14,97	0,20	4,19	1,31	1,21	12,48	2,74	**37,60***	**98,61***	1,20	2,04	66,43
	R	0,36	17,06	4,13	16,52	0,18	3,74	1,24	1,02	11,83	3,86	**34,85***	**71,67***	1,15	1,98	66,77
4	L	**0,78***	21,46	5,85	32,22	0,16	4,72	**1,38***	1,75	**13,42***	**2,70***	**44,07***	**130,35***	1,16	1,79	65,90
	R	**0,52***	23,31	5,71	37,07	0,12	4,59	**1,27***	1,60	**11,97***	**1,27***	**38,41***	**92,91***	1,15	1,77	63,40
5	L	**0,33***	**11,24***	3,18	**8,27***	0,24	3,88	1,27	1,06	**14,96***	4,42	**37,49***	**78,90***	1,14	1,93	60,77
	R	**0,20***	**13,51***	3,08	**11,19***	0,18	3,83	1,17	1,09	**12,33***	4,04	**33,56***	**61,41***	1,10	2,02	59,11
6	L	0,50	23,21	**5,91***	32,85	0,13	4,49	**1,34***	1,34	12,87	2,85	37,39	96,10	1,16	1,88	68,68
	R	0,57	25,11	**6,49***	35,87	0,14	4,99	**1,48***	1,69	12,33	3,34	36,24	82,75	1,19	1,92	72,40
7	L	0,34	13,95	3,30	11,80	0,13	4,30	1,14	1,13	**15,03***	2,99	36,20	62,14	**1,11***	2,02	**56,25**
	R	0,31	15,82	3,11	11,82	0,14	4,68	1,16	1,44	**12,97***	2,38	39,39	96,75	**0,94***	2,01	**49,85**
8	L	**0,35***	13,20	2,82	**8,10***	0,27	2,87	1,16	0,61	13,82	3,27	**30,31***	**54,90***	**1,34***	1,80	**79,93**
	R	**0,27***	14,23	2,84	**9,55***	0,31	2,70	1,17	0,62	13,81	3,91	**36,33***	**85,42***	**1,18***	1,70	**71,50**
9	L	**0,38***	**11,45***	3,10	**9,78***	**0,24***	**3,35***	**1,16***	**0,83***	**13,29***	1,37	**36,36***	**120,15***	1,07	1,67	68,15
	R	**0,22***	**13,95***	3,00	**13,40***	**0,13***	**2,75***	**0,91***	**0,58***	**8,54***	1,03	**21,44***	**29,55***	1,09	1,58	68,52
10	L	0,49	**20,06***	**4,59***	**20,55***	0,21	**4,49***	**1,54***	1,58	**15,65***	**3,69***	**42,48***	**143,71***	**0,98***	1,43	**67,95**
	R	0,41	**15,46***	**4,24***	**14,99***	0,23	**4,12***	**1,41***	1,22	**12,40***	**2,67***	**33,32***	**79,18***	**1,13***	1,43	**76,77**
11	L	**0,32***	13,93	**2,75***	**10,59***	**0,18***	3,80	1,01	**0,93***	13,38	1,93	32,28	75,16	1,00	1,94	55,23
	R	**0,20***	12,10	**2,28***	**7,49***	**0,27***	3,44	0,98	**0,70***	12,43	1,63	31,06	73,51	1,07	1,91	56,58
12	L	0,33	15,91	3,43	12,87	0,08	3,64	0,97	0,82	11,15	**3,86***	35,06	**70,38***	1,14	2,32	50,50
	R	0,27	17,06	3,26	14,00	0,06	3,50	0,94	0,82	10,76	**2,72***	37,62	**92,34***	1,15	2,28	50,66
13	L	0,45	17,25	3,68	14,98	0,11	4,40	**1,16***	1,26	13,63	2,86	44,67	165,56	1,16	2,18	55,63
	R	0,45	17,61	3,48	15,35	0,10	4,20	**1,05***	1,02	12,65	1,98	42,15	144,76	1,07	2,15	49,86
14	L	**0,64***	22,30	6,25	30,26	0,44	4,78	**1,88***	1,59	**15,25***	**1,74***	37,59	123,41	1,05	1,22	86,14
	R	**0,49***	20,31	6,22	30,07	0,49	4,57	**1,96***	1,59	**17,47***	**3,94***	37,23	91,10	1,08	1,21	90,90
15	L	**0,36***	10,50	2,96	7,09	0,13	3,89	1,16	1,02	14,69	**3,44***	41,94	135,77	1,12	1,97	55,57
	R	**0,26***	10,31	2,93	7,18	0,15	4,05	1,20	1,02	13,89	**2,36***	39,21	123,41	1,20	1,97	60,01
16	L	0,24	13,01	2,85	7,79	0,15	3,59	1,12	0,93	14,51	4,03	**45,06***	**158,54***	1,01	2,05	48,97

Table A.3: Intra-individual comparisons in the tandem walking backwards exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
	R	0,18	12,12	2,78	8,51	0,17	3,51	1,12	0,92	14,40	4,51	**36,63***	**73,31***	1,06	2,09	51,85
17	L	0,22	10,99	2,60	6,13	0,10	**3,45***	0,95	**0,67***	**13,53***	1,52	**35,87***	**112,09***	1,56	2,42	64,72
	R	0,17	9,90	2,59	6,27	0,13	**3,05***	0,90	**0,58***	**11,62***	1,28	**32,25***	**86,65***	1,59	2,36	67,16
18	L	0,23	15,17	3,14	12,14	0,16	**3,22***	0,99	**0,71***	**12,97***	3,24	**27,14***	35,76	**1,02***	1,94	**54,37**
	R	0,21	13,18	3,10	11,13	0,14	**2,79***	0,98	**0,61***	**10,55***	2,02	**22,82***	32,32	**1,18***	1,89	**62,12**
19	L	0,38	11,05	2,84	7,42	**0,13***	3,33	**1,08***	0,80	**13,60***	**3,07***	36,37	**83,76***	**1,06***	1,95	**54,95**
	R	0,33	11,15	3,02	7,92	**0,18***	3,36	**1,15***	0,82	**14,95***	**4,32***	34,57	**57,72***	**1,16***	1,96	**60,43**
20	L	0,39	**12,92***	3,01	9,73	0,12	4,57	1,19	**1,27***	**14,81***	2,55	**44,40***	**139,26***	**1,01***	**2,07***	**50,56**
	R	0,29	**11,73***	2,93	9,38	0,15	4,45	1,21	**1,17***	**15,98***	2,67	**49,29***	**182,75***	**0,97***	**2,09***	**46,61**
21	L	0,35	19,87	5,29	24,84	0,17	4,21	1,36	1,34	11,82	1,69	35,18	100,36	1,19	1,77	70,69
	R	0,32	19,69	5,38	27,66	0,18	4,44	1,51	1,50	12,79	3,37	36,87	101,45	1,30	1,80	75,16
22	L	0,45	15,71	4,89	17,32	**0,18***	3,98	1,49	1,11	16,44	2,05	36,97	85,27	1,12	1,45	78,21
	R	0,31	15,57	4,71	16,25	**0,25***	4,11	1,45	1,18	17,54	4,57	36,16	63,99	1,03	1,45	74,07
23	L	0,17	9,68	1,60	**2,87***	0,06	2,18	**0,55***	0,26	**11,02***	**4,48***	**25,82***	28,46	2,24	3,98	51,12
	R	0,13	10,33	1,54	**3,23***	0,05	1,98	**0,47***	0,19	**9,02***	**3,24***	**21,81***	24,70	1,83	3,67	44,04
24	L	**0,35***	11,62	**3,01***	**6,73***	0,09	3,05	1,08	0,75	14,50	2,57	46,96	**165,89***	1,36	2,16	62,57
	R	**0,24***	9,10	**2,70***	**4,90***	0,12	3,23	1,09	0,72	15,25	3,06	48,16	**185,67***	1,35	2,17	60,78
25	L	0,40	18,63	4,20	17,74	0,10	3,48	1,10	0,85	10,97	2,21	31,22	72,62	0,99	1,67	59,63
	R	0,29	16,40	4,46	19,16	0,12	3,80	1,14	0,84	11,90	2,33	32,39	64,53	1,18	1,68	68,35
26	L	0,25	15,78	4,01	19,52	0,10	4,03	1,14	**1,16***	12,52	5,17	30,63	45,25	1,33	2,04	63,00
	R	0,27	16,47	4,32	22,66	0,12	3,71	1,10	**0,96***	12,83	4,87	31,03	51,38	1,37	2,08	68,57
27	L	**0,38***	**9,82***	2,55	**5,73***	0,08	2,54	0,89	**0,46***	**12,29***	**3,05***	**34,21***	75,91	**1,42***	2,28	**61,23**
	R	**0,16***	**7,19***	2,33	**4,09***	0,14	2,27	0,84	**0,34***	**10,64***	**1,21***	**28,49***	74,70	**1,78***	2,29	**76,54**
28	L	0,32	15,02	4,19	12,33	0,16	3,76	**1,29***	1,03	**18,37***	3,14	**51,81***	**236,08***	1,13	1,64	**69,42**
	R	0,27	15,13	4,02	13,08	0,14	3,71	**1,21***	0,97	**15,32***	2,00	**44,84***	**161,25***	1,09	1,63	**65,47**

* Significant difference for $p < 0,05$

A.4 Heel walking exercise

Table A.4: Intra-individual comparisons in the heel walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
1	L	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
	R	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2	L	0,30	19,56	5,16	30,13	0,30	3,56	1,26	0,96	1,68	24,08	13,44	41,07	0,86	1,02	**91,87**
	R	0,26	16,14	4,71	23,49	0,36	3,16	1,28	0,79	3,19	25,09	13,98	43,79	0,93	0,99	**98,25**
3	L	0,32	22,74	6,62	33,96	**0,46***	3,99	1,65	1,12	1,73	**26,02***	**11,58***	**50,41***	0,99	1,13	95,90
	R	0,38	23,52	6,57	34,46	**0,39***	3,77	1,58	0,97	2,18	**32,62***	**14,58***	**79,57***	1,04	1,16	96,06
4	L	0,37	24,85	8,21	54,18	0,40	5,34	2,09	2,27	1,98	38,47	17,16	103,90	1,11	1,26	95,83
	R	0,31	25,20	7,89	47,92	0,42	4,85	1,93	1,60	2,72	36,53	16,91	90,88	1,10	0,98	95,30
5	L	0,26	18,91	5,64	28,68	0,49	4,12	1,70	1,20	2,84	**28,73***	**14,03***	**60,02***	1,03	1,30	89,45
	R	0,18	20,18	5,82	33,36	0,38	4,77	1,73	1,63	2,19	**34,28***	**16,26***	**77,82***	1,04	1,29	92,99
6	L	0,27	18,17	5,61	26,46	0,32	4,20	1,53	1,36	**1,53***	**32,77***	**14,54***	82,74	1,19	1,33	87,59
	R	0,23	20,80	5,38	27,94	0,39	4,28	1,60	1,37	**3,14***	**37,08***	**17,57***	91,68	1,15	1,34	83,76
7	L	0,18	12,00	3,16	10,25	0,27	4,97	1,34	1,51	3,15	41,01	17,14	106,29	1,01	2,11	49,02
	R	0,20	13,40	3,13	10,94	0,28	4,88	1,33	1,46	3,81	36,91	15,61	89,04	1,09	2,07	52,29
8	L	**0,27***	**10,19***	2,79	**8,57***	0,28	2,80	0,97	0,50	1,64	21,61	**10,86***	**31,55***	1,05	1,43	76,88
	R	**0,20***	**13,32***	3,12	**12,67***	0,25	3,11	1,05	0,72	1,02	21,91	**9,96***	**38,41***	1,07	1,39	78,72
9	L	0,22	**17,97***	**4,20***	**19,30***	0,30	**4,37***	**1,46***	**1,38***	1,81	**31,17***	13,53	**75,08***	1,02	1,38	75,18
	R	0,18	**13,98***	**3,79***	**13,99***	0,33	**3,77***	**1,37***	**1,05***	2,42	**27,15***	12,98	**54,78***	1,05	1,37	76,75
10	L	0,33	27,90	8,12	62,00	**0,31***	**4,65***	**1,74***	**1,54***	1,36	31,29	13,99	71,25	0,86	**0,95***	98,04
	R	0,34	27,20	7,96	61,53	**0,45***	**5,35***	**1,96***	**2,02***	2,16	32,34	14,91	67,87	0,86	**0,91***	94,71
11	L	0,23	13,68	3,47	13,80	0,23	**3,17***	1,10	0,67	1,30	21,00	9,56	31,88	1,06	1,43	78,47
	R	0,19	17,57	4,00	22,76	0,25	**4,43***	1,18	1,15	1,27	22,41	9,51	35,47	1,00	1,44	72,81
12	L	**0,24***	15,71	4,04	18,51	**0,31***	3,44	1,19	0,92	**0,86***	25,21	12,41	45,08	1,04	1,22	86,91
	R	**0,13***	15,45	3,84	16,28	**0,21***	3,43	1,20	0,99	**1,55***	24,17	12,48	37,75	1,04	1,25	86,16
13	L	0,25	17,45	4,86	21,45	0,34	4,58	1,49	1,37	2,46	34,82	16,62	92,83	1,06	1,49	82,58
	R	0,21	17,41	5,11	25,69	0,28	4,84	1,56	1,54	2,49	34,65	15,25	89,35	1,12	1,48	82,42
14	L	0,29	20,07	5,74	32,92	0,30	4,24	1,51	1,39	1,45	**25,82***	**12,35***	**50,32***	1,06	1,17	92,69
	R	0,25	22,78	6,16	37,24	0,34	4,40	1,61	1,42	1,92	**35,35***	**17,07***	**91,99***	1,05	1,21	94,22
15	L	**0,25***	**9,18***	**2,82***	**7,33***	0,24	2,70	0,97	0,59	1,91	**21,10***	11,72	**32,05***	1,16	1,41	83,15
	R	**0,18***	**12,01***	**3,12***	**11,30***	0,25	2,91	0,97	0,61	1,92	**24,49***	11,81	**43,91***	1,14	1,48	80,45
16	L	**0,33***	12,09	3,21	11,46	0,24	2,85	0,98	0,56	1,63	19,73	**9,48***	25,27	1,19	1,53	80,68

Table A.4: Intra-individual comparisons in the heel wallking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
	R	**0,16***	9,15	2,65	6,67	0,18	2,46	0,87	0,39	1,54	20,77	**10,24***	29,77	1,23	1,51	82,49
17	L	0,29	20,22	5,77	27,94	0,29	4,29	1,71	1,42	2,53	**29,90***	12,17	**69,47***	1,03	1,05	97,28
	R	0,23	21,27	5,81	30,66	0,32	4,34	1,67	1,51	1,94	**25,76***	11,45	**55,45***	1,00	1,10	94,44
18	L	**0,28***	14,26	**4,85***	**19,22***	0,41	**4,19***	**1,50***	**1,28***	1,55	31,65	15,58	79,73	**1,25***	1,59	**77,97**
	R	**0,18***	12,94	**4,05***	**13,19***	0,32	**3,18***	**1,23***	**0,63***	1,16	33,46	15,29	89,51	**1,34***	1,59	**84,48**
19	L	0,24	12,77	3,98	**13,60***	0,35	2,48	1,02	0,36	1,82	25,80	12,39	**55,95***	1,08	1,13	92,57
	R	0,21	13,55	4,17	**15,51***	0,26	2,57	0,99	0,42	1,10	24,46	11,27	**47,24***	1,10	1,18	94,15
20	L	**0,33***	11,65	3,74	11,04	0,28	**2,68***	1,18	0,55	1,26	**22,97***	**10,71***	**39,15***	**1,22***	1,33	**93,26**
	R	**0,17***	12,82	3,86	14,18	0,33	**2,99***	1,21	0,65	1,22	**26,35***	**11,56***	**51,05***	**1,15***	1,35	**87,44**
21	L	0,38	**25,68***	7,44	47,52	0,34	5,37	2,07	1,98	0,85	30,86	13,36	81,36	0,98	1,08	96,51
	R	0,39	**23,17***	7,07	40,25	0,36	5,22	1,97	1,83	1,59	31,45	13,04	79,67	1,00	1,08	97,16
22	L	0,36	**14,46***	**4,49***	16,79	**0,24***	**3,30***	**1,22***	**0,70***	1,74	21,49	9,82	**32,48***	1,21	1,35	**84,68**
	R	0,33	**16,29***	**4,90***	17,04	**0,38***	**2,37***	**1,08***	**0,34***	1,92	20,01	10,01	**25,21***	1,24	1,32	**93,54**
23	L	0,37	13,76	3,87	10,90	0,18	2,56	1,05	0,42	6,10	31,35	**15,54***	60,65	1,29	1,84	79,50
	R	0,30	13,63	3,71	10,24	0,24	2,41	0,99	0,39	5,72	33,24	**16,89***	74,24	1,36	1,83	80,85
24	L	**0,42***	**19,45***	5,67	**28,18***	0,37	3,19	**1,51***	**0,83***	**5,04***	**30,38***	**15,63***	**54,17***	1,10	1,20	**95,38**
	R	**0,32***	**14,92***	5,31	**19,48***	0,32	3,01	**1,37***	**0,63***	**2,71***	**25,37***	**11,91***	**46,94***	1,13	1,13	**97,87**
25	L	**0,20***	18,24	4,98	24,30	0,37	**3,40***	1,52	0,97	**3,08***	29,88	13,68	55,25	**1,11***	1,24	**92,60**
	R	**0,14***	19,17	4,91	25,29	0,31	**3,82***	1,44	1,12	**0,85***	27,67	12,17	53,91	**1,05***	1,26	**86,20**
26	L	0,29	11,90	4,14	12,31	0,34	3,27	**1,24***	**0,77***	1,77	28,32	14,01	53,97	1,40	1,71	80,31
	R	0,28	13,43	4,42	15,19	0,25	3,79	**1,36***	**1,05***	2,02	30,82	14,41	63,20	1,36	1,71	77,56
27	L	3,68	3,14	0,26	2,34	1,04	**0,70***	5,77	**10,79***	28,31	1,28	21,03	89,28	10,72	0,71	1,44
	R	0,29	12,66	3,69	10,13	0,25	**2,04***	0,99	**0,28***	2,19	19,99	9,66	27,90	1,31	1,48	91,78
28	L	0,23	12,91	4,02	12,32	0,26	3,19	1,31	0,72	**1,16***	23,84	**10,55***	53,23	1,22	1,37	89,77
	R	0,19	12,59	4,08	12,75	0,29	3,30	1,30	0,74	**2,78***	25,33	**12,53***	45,57	1,18	1,36	86,66

* Significant difference for $p < 0,05$

A.5 Toe walking exercise

Table A.5: Intra-individual comparisons in the toe walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
1	L	0,57	22,78	6,49	35,94	**0,39***	4,86	**1,87***	1,75	**2,67***	37,54	15,58	99,85	1,05	1,19	89,60
	R	0,72	23,77	6,76	35,06	**0,34***	5,19	**2,05***	2,02	**1,43***	38,49	15,73	107,40	1,07	1,18	90,42
2	L	**0,21***	19,69	5,44	28,91	0,35	4,89	1,85	1,82	**0,87***	**49,68***	**19,07***	181,87	1,06	1,36	84,70
	R	**0,37***	20,66	5,67	31,04	0,29	4,82	1,82	1,74	**2,67***	**44,97***	**15,91***	160,93	1,07	1,18	86,30
3	L	0,70	39,94	10,07	85,61	0,55	**6,58***	2,62	**3,03***	3,14	46,91	19,90	164,34	0,77	0,98	85,77
	R	0,70	42,07	10,05	94,92	0,61	**6,06***	2,53	**2,56***	2,89	49,03	20,28	164,05	0,75	0,98	82,15
4	L	0,68	23,87	8,38	40,82	0,46	5,96	2,53	2,78	1,40	52,57	20,26	231,01	1,20	**0,58***	94,52
	R	0,53	26,31	8,78	47,99	0,38	5,93	2,41	2,89	2,25	53,48	20,93	211,76	1,20	**1,31***	93,80
5	L	0,49	28,30	7,25	48,91	0,56	5,32	2,13	**2,08***	**5,98***	43,61	**21,25***	**83,61***	0,98	1,06	93,26
	R	0,41	29,15	6,80	46,94	0,58	5,00	2,01	**1,76***	**2,00***	43,42	**16,76***	**153,82***	0,96	1,14	91,50
6	L	0,40	21,65	6,84	34,23	0,22	**5,08***	2,00	**2,22***	2,12	**54,58***	21,24	**219,66***	1,25	**0,49***	89,00
	R	0,43	21,55	6,87	33,86	0,16	**5,63***	2,02	**2,50***	1,99	**52,37***	19,91	**182,44***	1,21	**1,41***	86,98
7	L	0,30	13,03	3,60	10,74	0,19	4,30	1,46	1,43	2,06	40,67	**15,28***	**123,54***	1,01	1,75	58,67
	R	0,24	11,71	3,60	9,78	0,27	4,17	1,46	1,22	3,26	42,74	**20,58***	**86,15***	1,07	1,73	60,37
8	L	0,21	**11,38***	**2,91***	**7,64***	**0,28***	**3,86***	**1,28***	**0,99***	1,05	**38,80***	**15,76***	**81,73***	**1,07***	1,61	**67,38**
	R	0,30	**14,07***	**3,23***	**13,21***	**0,22***	**4,17***	**1,23***	**1,20***	1,30	**41,13***	**14,96***	**107,88***	**0,91***	1,58	**55,84**
9	L	0,34	18,45	4,71	23,88	**0,20***	**4,71***	1,44	1,51	1,66	35,93	13,69	103,36	0,87	1,29	69,62
	R	0,47	20,97	4,82	24,77	**0,30***	**4,27***	1,45	1,27	1,51	36,54	13,28	107,66	0,82	1,29	67,05
10	L	0,56	33,53	10,07	79,53	0,61	**6,75***	2,43	**3,37***	2,14	**51,73***	**20,11***	**207,95***	0,86	0,91	98,29
	R	0,54	33,09	10,25	79,11	0,48	**7,40***	2,62	**3,95***	2,72	**46,05***	**18,57***	**156,54***	0,84	0,89	95,54
11	L	0,37	14,24	3,42	11,21	0,21	**3,94***	1,30	**1,24***	2,14	42,33	17,19	127,48	1,03	1,38	**73,44**
	R	0,34	15,62	3,62	15,88	0,17	**4,77***	1,26	**1,55***	3,44	41,89	16,56	113,63	0,94	1,46	**64,63**
12	L	**0,42***	16,65	3,75	14,76	0,10	3,67	1,26	1,25	1,39	45,22	15,65	168,93	1,12	1,40	76,05
	R	**0,27***	14,13	3,66	12,85	0,14	3,66	1,25	1,21	1,01	42,97	14,34	146,45	1,07	1,47	72,38
13	L	0,52	26,15	**8,50***	51,36	**0,37***	**6,93***	2,50	**3,62***	2,42	58,03	22,28	248,68	1,11	0,89	92,13
	R	0,43	25,37	**7,56***	42,38	**0,25***	**6,18***	2,50	**3,06***	2,20	57,57	23,02	239,13	1,13	1,26	92,74
14	L	0,54	22,94	6,70	38,19	0,30	4,94	1,74	2,10	3,49	**49,44***	**20,41***	**151,47***	1,05	1,20	84,49
	R	0,48	28,43	7,05	53,58	0,31	5,15	1,79	2,14	3,93	**42,97***	**17,07***	**112,03***	1,00	1,19	84,07
15	L	0,28	**11,11***	**3,76***	**10,19***	0,28	**4,49***	1,47	**1,53***	**1,28***	46,67	16,70	**151,62***	0,99	1,52	**64,49**
	R	0,29	**13,37***	**4,10***	**14,03***	0,20	**4,75***	1,46	**1,62***	**1,98***	45,64	16,75	**134,23***	0,92	1,57	**59,41**
16	L	0,23	10,97	2,69	7,55	0,23	**3,13***	**1,00***	**0,66***	**4,67***	43,00	**18,18***	129,57	0,96	1,74	54,46

Table A.5: Intra-individual comparisons in the toe walking exercise. L and R identify the mean values of the left and right limb, respectively. Participants numbered 1 to 14 belonged to group 1 and participants numbered 15 to 28 were part of the group 2.

Participant	Limb	Acceleration minimum	Acceleration maximum	Acceleration mean	Acceleration variance	Angular velocity minimum	Angular velocity maximum	Angular velocity mean	Angular velocity variance	SVA minimum	SVA maximum	SVA mean	SVA variance	Non-stationary phase duration	Stationary phase duration	Non-stationary phase (% of GC)
	R	0,22	11,15	2,71	6,77	0,22	**3,67***	**1,08***	**0,81***	**1,50***	41,52	**15,03***	131,89	0,91	1,72	53,08
17	L	0,61	**25,52***	7,45	37,65	0,45	**5,70***	2,22	2,30	5,45	**47,75***	**21,09***	**166,02***	1,01	1,05	95,82
	R	0,57	**20,94***	7,62	33,77	0,44	**5,46***	2,23	2,24	4,42	**42,02***	**17,91***	**123,96***	0,99	1,12	95,31
18	L	0,42	19,21	6,11	24,94	**0,26***	**4,85***	1,95	1,90	**1,27***	54,05	**22,00***	207,06	1,34	0,93	84,18
	R	0,45	19,65	6,07	26,53	**0,40***	**4,69***	2,02	1,92	**2,33***	53,19	**20,55***	188,15	1,29	1,18	81,44
19	L	0,44	20,49	5,44	26,53	**0,39***	5,20	1,96	**2,11***	1,15	**46,31***	**16,74***	**181,55***	**1,01***	1,15	**83,96**
	R	0,45	19,34	5,40	25,24	**0,47***	4,96	1,87	**1,84***	1,14	**40,99***	**15,35***	**132,48***	**1,04***	1,22	**87,16**
20	L	0,39	23,08	7,12	38,42	0,43	5,80	2,27	2,43	1,86	51,66	20,47	217,72	**1,08***	**1,18***	**93,87**
	R	0,43	25,78	6,85	40,23	0,44	5,62	2,21	2,55	1,37	50,09	19,01	215,85	**1,05***	**1,19***	**89,87**
21	L	0,77	23,89	8,03	33,85	0,46	6,32	2,46	2,90	1,73	41,56	18,30	137,23	0,99	1,07	95,21
	R	0,69	22,75	7,24	35,27	0,47	5,93	2,39	2,66	1,51	41,79	18,61	127,98	1,02	1,14	96,34
22	L	0,79	26,35	9,43	52,83	0,51	5,22	2,14	2,05	2,56	32,68	14,38	83,37	0,99	1,01	98,38
	R	0,56	20,93	7,47	31,54	0,50	4,48	1,99	1,43	4,42	30,04	15,76	55,93	1,04	1,25	88,93
23	L	0,48	27,75	5,97	38,55	0,35	4,19	1,69	1,47	1,36	42,99	15,54	156,11	1,08	1,41	80,68
	R	0,49	27,51	6,24	43,11	0,27	4,41	1,66	1,66	1,28	44,85	15,91	163,60	1,09	1,39	83,16
24	L	0,53	**26,38***	**8,20***	**50,29***	0,39	**5,79***	**2,25***	**2,83***	**3,61***	**60,42***	**23,85***	**283,46***	**1,07***	1,19	**92,24**
	R	0,44	**20,30***	**6,90***	**29,87***	0,34	**4,56***	**1,94***	**1,75***	**1,59***	**48,20***	**18,67***	**175,59***	**1,13***	1,22	**95,95**
25	L	**0,36***	21,39	**6,23***	32,38	0,40	**4,80***	1,95	**2,06***	**1,40***	55,68	**19,00***	**249,00***	1,08	1,26	83,81
	R	**0,58***	22,28	**6,78***	35,12	0,35	**5,22***	1,95	**2,27***	**4,82***	54,30	**22,27***	**184,07***	1,05	1,30	82,34
26	L	0,30	**13,50***	**4,07***	**13,11***	0,20	**4,30***	1,49	**1,35***	2,51	**49,97***	20,91	**162,96***	1,20	1,75	67,11
	R	0,28	**16,04***	**4,63***	**19,95***	0,25	**5,01***	1,56	**1,71***	1,97	**52,95***	21,07	**186,05***	1,14	1,75	65,75
27	L	0,23	11,89	4,10	10,02	**0,18***	3,76	1,53	1,10	**1,66***	47,34	**18,76***	**148,05***	1,42	1,78	81,10
	R	0,22	11,23	4,18	9,89	**0,37***	3,89	1,55	1,04	**6,73***	47,20	**21,63***	**120,64***	1,40	1,74	82,93
28	L	0,69	**16,09***	5,85	19,60	0,34	5,50	**2,07***	**2,30***	2,24	**43,03***	18,00	**144,57***	1,07	1,36	79,34
	R	0,67	**19,70***	5,82	22,74	0,35	5,36	**1,90***	**1,99***	1,88	**44,44***	17,97	**154,16***	1,09	1,36	79,42

* Significant difference for $p < 0,05$